ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

ENHANCING HUMAN RESOURCE DECISION MAKING WITH IMAGE-BASED OSMI DATA ANALYSIS: LEVERAGING PIX2PIX FOR ACCURATE WORKPLACE MENTAL HEALTH INSIGHTS

M.Sc. THESIS

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ISTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

İŞ YERİ MENTAL SAĞLIK İNCELEMELERİ İÇİN PIX2PIX KULLANARAK, GÖRÜNTÜ TABANLI OSMI VERİ ANALİZİYLE İNSAN KAYNAKLARI KARAR SÜREÇLERİNİ GELİŞTİRME

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Fariba FARID, a M.Sc. student of ITU Graduate School student ID 507201211 successfully defended the thesis entitled "ENHANCING HUMAN RESOURCE DECISION MAKING WITH IMAGE-BASED OSMI DATA ANALYSIS: LEVERAGING PIX2PIX FOR ACCURATE WORKPLACE MENTAL HEALTH INSIGHTS", which he/she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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To my family and my beloved spouse, Yaser,

FOREWORD

I would like to express my gratitude to the individuals who have supported me throughout my Master's thesis journey in various ways.

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TABLE OF CONTENTS

ABBREVIATIONS

AI	: Artificial Intelligence
AIM	: Artificial Intelligence in Medical
CMDs	: Common Mental Disorders
DL	: Deep Learning
GANs	: Generative adversarial networks
IT	: Information Technology
KDD	: Knowledge Discovery in Databases
MHD	: Mental Health Disorder
ML	: Machine Learning
MHI	: Mental Health Image
MAE	: Mean Absolute Error
MSE	: Mean Squared Error
OSMI	: Open Source Mental Illness
PSNR	: Peak Signal-to-Noise Ratio
RMSE	: Root Mean Square Error
SAM	: Spectral Angle Mapper
SSIM	: Structural Similarity Index Measure
SRE	: Signal-to-Reconstruction-Error Ratio
UIQ	: Universal Image Quality Index
WHO	: The World Health Organization

SYMBOLS

D	: Discriminator
G	: Generator
$P_{\mathbf{data(x)}}$	: Distribution of real data
$P(z)$	: Distribution of generator,
x	: Sample from $P_{\text{data(x)}}$
z	: Sample from $P(z)$
$D(x)$	: Discriminator Network
$G(z)$	: Generator Network
$\min\limits_{G}$	: Minimization of Generator Network
$\max\limits_{D}$	: Maximization of Discriminator Network
$\mathscr{L}_{\mathbf{GAN}}(D,G)$	: Adversarial Loss
λ	: Hyperparameter
$\mathscr{L}_{\mathbf{L1}}(G)$	: L1 loss
M , N	: Dimensions of the images
$S(i,j)$	: Pixel Value of source image at location (i,j)
$G(i,j)$	: Pixel Value of generated image at location (i,j)
MAX_I	: Maximum possible pixel value of image
MSE	: Mean Squared Error between source and generated images
μ_x , μ_y	: Means of the respective pixel values
σ_x , σ_y	: Standard Deviations
σ_{xy}	: Covariance
C_1 , C_2	: Constants
μ_{I_i} , μ_{K_i}	: Means Intensities
$\sigma^2_{I_i}$, $\sigma^2_{K_i}$	: Variances Intensities
$\sigma_{I_iK_i}$	: Covariance Intensities

LIST OF TABLES

LIST OF FIGURES

Page

ENHANCING HUMAN RESOURCE DECISION MAKING WITH IMAGE-BASED OSMI DATA ANALYSIS: LEVERAGING PIX2PIX FOR ACCURATE WORKPLACE MENTAL HEALTH INSIGHTS

SUMMARY

Mental health issues have become increasingly prevalent and severe in today's society, negatively impacting all aspects of individuals' lives. Artificial intelligence (AI) and its subfields, such as Machine Learning (ML) and Deep Learning (DL), have widespread applications in many domains. These invaluable tools have been widely utilized in various companies to identify mental health disorders and their effects on their employees and workplaces. Many studies have used machine learning models to identify factors that contribute to mental disorders. This study, however, takes a new approach by generating predicted images of mental health disorders among the Tech Survey population. This research provides valuable insights into mental health disorders in the technology industry, which can be used by human resource departments and company leaders to support employees and enhance productivity. Ultimately, this can create a mutually beneficial relationship between workers and employers. The Pix2Pix GAN model is used as a novel technique for the Open Sourcing Mental Illness (OSMI) application. The dataset used in this study comprises over 1484 responses collected via Google Forms during 2017, 2018, 2020, and 2021. This approach acquires further valuable insights on how to make decisions for employees who experience mental health disorders by processing and evaluating data. Preprocessing and scaling the data is a crucial step in Knowledge Discovery in Databases (KDD) as it is challenging to analyze raw data. In this study, the data was preprocessed and scaled before being transformed into images where each pixel represents an attribute.

This dataset mainly consists of male individuals residing in the United States who are employed in the technology industry. This is in line with the reality that men hold a greater proportion of positions in the tech industry than women, and It is widely believed that mental health disorders have a negative impact on work performance and productivity in this industry.

The thesis highlighted the importance of understanding the characteristics of the questions answered in the data. To achieve this, a close examination of the content was conducted, analyzing various attributes. The survey included different types of questions, such as general, workplace-related, and personal. While the dataset had limited data quality information, it was well-documented. It would have been beneficial to have information on the types of tech companies where participants worked to compare attitudes toward mental health across different sectors. The Mental Health Tech Survey provided useful psychometric variables, which were further categorized and discussed in the thesis.

In this study, a significant innovation is the transformation of structured data into unstructured data. This involves changing data that is organized in a specific format,a tabular data, into a format that is not pre-defined, an images. The main aim of this conversion is to enhance data accessibility, improve analysis, and make it more useful for decision-making. To achieve this, the questions were divided into general feature questions asked of employees overall, and questions that are particularly valuable for human resources to gain insights about their employees, such as whether they talk about mental disorders during interviews. These questions contained more self-reported answers that even employees may not be aware of as indicating mental illness. The model was then trained to map the input feature picture to the output label picture, generating a new image that corresponds to the input feature picture.

As a result,in this case, the input feature picture represents an individual's answers to questions related to mental health disorders, while the output label picture represents the labels that are more relevant in diagnosing mental disorders based on previous studies.

The process of selecting questions as labels or features in the context of tech surveys plays a crucial role in recognizing individuals with disorders and understanding mental health. These questions consider various factors that aid in identifying individuals with disorders, such as self-reporting their condition, comfort in discussing it with employers, seeking treatment, and the impact of the disorder on their lives. Additionally, the selected questions provide insights into how mental health is perceived among employees in the tech industry, allowing for a better understanding of attitudes, norms, and challenges in this context. The focus is on a holistic evaluation that considers the overall well-being of individuals, rather than specific disorders. The self-reported nature of the questions is essential as it reveals how individuals identify themselves and their preferences regarding disclosure. This information helps human resource professionals make informed decisions during the hiring process and provide tailored support to optimize employee performance and well-being.

The pix2pix GAN model was then evaluated on a dataset of 1458 images using both quantitative metrics, such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Peak Signal-to-noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), Signal-to-reconstruction Error Ratio (SRE), Spectral Angle Mapper (SAM), and Universal Image Quality Index (UIQ), and qualitative inspection. The results showed that the model was capable of generating high-quality images efficiently.

In order to determine the best model for GAN training and prevent overfitting, the dataset was split into three sets: train, test, and validation. The optimal epoch for all sets was determined by visually inspecting the images, comparing various quantitative metrics and visualization methods, and the best epoch was found to be epoch 30.

The results of this study indicate that the pix2pix GAN model is a beneficial tool for creating high-quality Mental Health Images (MHI), which may have innovative uses in identifying valuable information. By using images instead of lengthy questionnaires, HR employers can quickly obtain the desired information. Furthermore, the findings reveal a significant correlation between individuals who disclose their mental health issues to potential employers during interviews, mental health conditions that impair their job performance, and individuals with a family history of mental illness . These results could support suggested visionary aims for HR departments to help potential employees who believe that their mental health issues may affect their productivity or performance at work.

The predictive capability of the pix2pix GAN holds value for human resource professionals as it can potentially aid in identifying or predicting mental health conditions in employees based on available data. This tool can facilitate the decision-making process for HR professionals and enable early intervention or targeted support to enhance employees' mental well-being.

IŞ YERİ MENTAL SAĞLIK İNCELEMELERİ İÇİN PIX2PIX KULLANARAK, GÖRÜNTÜ TABANLI OSMI VERİ ANALİZİYLE İNSAN KAYNAKLARI KARAR SÜREÇLERİNİ GELİŞTİRME

ÖZET

Zihinsel sağlık sorunları günümüz toplumunda giderek daha yaygın ve ciddi bir hal almış olup, bireylerin yaşamlarının tüm yönlerini olumsuz etkilemektedir. Yapay zeka (AI) ve onun alt alanları olan Makine Öğrenimi (ML) ve Derin Öğrenme (DL), birçok alanda yaygın olarak kullanılmaktadır. Bu değerli araçlar, çeşitli şirketlerde çalışanların ve işyerlerinin zihinsel sağlık bozukluklarını tespit etmek için yaygın bir şekilde kullanılmaktadır.

Birçok çalışma, zihinsel bozukluklara katkıda bulunan faktörleri belirlemek için makine öğrenimi modellerinden yararlanmıştır. Ancak bu çalışma, Tech Survey popülasyonu arasında zihinsel sağlık bozukluklarının tahmin edilen görüntülerini oluşturarak yeni bir yaklaşım benimsemektedir.

Bu araştırma, teknoloji endüstrisindeki zihinsel sağlık bozuklukları hakkında değerli içgörüler sağlamaktadır ve insan kaynakları departmanları ile şirket liderleri tarafından çalışanları desteklemek ve verimliliği artırmak için kullanılabilir. Sonuç olarak, bu çalışma işçiler ve işverenler arasında karşılıklı fayda sağlayan bir ilişki yaratmayı amaçlamaktadır. Pix2Pix GAN modeli, Open Sourcing Mental Illness (OSMI) uygulamasında yeni bir teknik olarak kullanılmaktadır. Bu çalışmada kullanılan veri seti, 2017, 2018, 2020 ve 2021 yılları arasında Google Forms aracılığıyla toplanan 1484 yanıttan oluşmaktadır.

Veri kalitesi hakkındaki mevcut bilgiler kapsamlı değildir, ancak veri kümesi detaylı bir belgelendirme ile birlikte sunulmaktadır. Katılımcıların çalıştığı teknoloji şirketlerinin belirli türleri hakkında bilgi sağlanmış olsaydı faydalı olurdu.

Bu yaklaşım, zihinsel sağlık sorunları yaşayan çalışanlar için veri işleme ve değerlendirme yoluyla kararlar almak için daha fazla değerli içgörü sağlar. Veri ön işleme ve ölçeklendirme, Veritabanında Bilgi Keşfi (KDD) sürecinde zorlu bir adımdır çünkü ham veriyi analiz etmek zordur. Bu çalışmada veri, her pikselin bir özelliği temsil ettiği görüntülere dönüştürülmeden önce ön işlemden geçirilmiş ve ölçeklendirilmiştir.

Büyük veri kümeleriyle çalışırken, özel karakterlerin, eksik değerlerin ve boşlukların varlığı önerilen modele etki edebilir. Bu karakterlerin, hazırlık sürecinde temel bilgileri korumak ve manipüle etmemek için dikkatlice işlenmesi gerekmektedir. Veri kaynağının tutarlılığına rağmen, tüm yıllar boyunca veri tutarlılığı konusunda bazı sorunlar yaşandı.

Bu veri seti, teknoloji endüstrisinde çalışan ve Amerika Birleşik Devletleri'nde yaşayan erkek bireylerden oluşmaktadır. Bu durum, erkeklerin teknoloji endüstrisinde

kadınlara kıyasla daha büyük bir oranda pozisyon sahibi olduğu gerçeğiyle uyumludur ve zihinsel sağlık bozukluklarının bu endüstride iş performansı ve verimlilik üzerinde olumsuz bir etkisi olduğu genel olarak kabul edilmektedir.

Tez, verilerdeki soruların özelliklerini anlamanın önemini vurgulamaktadır. Bunun için içeriğin yakından incelenmesi ve çeşitli özelliklerin analiz edilmesi gerekmektedir. Anket, genel, işyeriyle ilgili ve kişisel gibi farklı tipte sorular içermektedir. Veri seti sınırlı veri kalite bilgisine sahip olmasına rağmen, iyi belgelenmiştir.

Katılımcıların çalıştığı teknoloji şirketlerinin türleri hakkında bilgi sağlanması farklı sektörler arasında zihinsel sağlık konusundaki tutumları karşılaştırmak açısından faydalı olabilirdi. Mental Sağlık Teknolojisi Anketi, tezde daha ileri kategorilere ayrılan ve tartışılan faydalı psikometrik değişkenler sunmaktadır.

Bu çalışmada önemli bir yenilik, yapılandırılmış verilerin yapılandırılmamış verilere dönüştürülmesidir. Bu, belirli bir formatta düzenlenmiş verilerin, tablo verisi olarak bilinen bir formattan önceden tanımlanmamış bir görüntü formatına dönüştürülmesini içerir. Bu dönüşümün temel amacı, veriye erişilebilirliği artırmak, analizi geliştirmek ve karar verme süreçlerinde daha kullanışlı hale getirmektir. Bunun için sorular, genel olarak çalışanlara yöneltilen genel özellik soruları ve insan kaynakları açısından çalışanlar hakkında içgörü elde etmek için değerli olan sorular olmak üzere ikiye ayrılmıştır.

Bu sorular, çalışanların mülakatlar sırasında zihinsel bozukluklar hakkında konuşup konuşmadıklarını da içeren, hatta çalışanların bile farkında olmadığı kendilik bildirilen yanıtları içermektedir. Model daha sonra girdi özellik görüntüsünü çıktı etiket görüntüsüne eşlemek üzere eğitilmiş ve girdi özellik görüntüsüne karşılık gelen yeni bir görüntü üretmektedir.

Sonuç olarak, bu durumda girdi özellik görüntüsü, zihinsel sağlık bozukluklarıyla ilgili sorulara verilen bireyin cevaplarını temsil etmektedir, oysa çıktı etiket görüntüsü, daha önce yapılan çalışmalara dayanarak zihinsel bozuklukların teşhisinde daha ilgili olan etiketleri temsil etmektedir.

Teknoloji anketleri bağlamında soruların etiket veya özellik olarak seçilme süreci, bireylerin bozukluklarını tanıma ve ruh sağlığını anlama konusunda kritik bir rol oynar. Bu sorular, bireylerin durumlarını kendilerinin bildirmesi, işverenlerle konuşmalarında rahatlık, tedavi arayışı ve bozukluğun yaşamlarına olan etkisi gibi çeşitli faktörleri dikkate alır. Ayrıca, seçilen sorular, teknoloji endüstrisinde çalışanlar arasında ruh sağlığının nasıl algılandığı konusunda içgörüler sağlar, bu da bu bağlamda tutumlar, normlar ve zorluklar hakkında daha iyi bir anlayış sağlar. Odak noktası, belirli bozukluklar yerine bireylerin genel refahını göz önünde bulunduran bütüncül bir değerlendirmedir.

Soruların kendini bildirme niteliği, bireylerin kendilerini nasıl tanımladıklarını ve açıklama konusundaki tercihlerini ortaya koyduğu için önemlidir. Bu bilgi, insan kaynakları profesyonellerinin işe alma sürecinde bilinçli kararlar vermelerine ve çalışan performansını ve refahını optimize etmek için özelleştirilmiş destek sağlamalarına yardımcı olur.

Pix2Pix, görüntüden görüntüye çeviri görevleri için tasarlanmış bir derin öğrenme modelidir. 2016 yılında California Üniversitesi, Berkeley'deki araştırmacılar tarafından önerilmiştir. Model, jeneratif modellerin gücünü ve karşıtlıklı eğitimi bir araya getiren bir koşullu jeneratif düşmanlıklı ağ (cGAN) mimarisinden yararlanır. Pix2Pix'in temel amacı, giriş görüntüleri ile karşılık gelen çıkış görüntüleri arasında bir eşleme öğrenmektir. Bu, her giriş görüntüsünün istenen çıkış görüntüsüyle eşleştirildiği çiftli eğitim verilerini gerektiren bir denetimli öğrenme yaklaşımıdır. Bu özellik, görüntü renklendirme, stil transferi, anlamsal bölütleme gibi görevler için uygundur.

Pix2Pix, çeşitli görüntü çeviri görevlerinde dikkate değer sonuçlar elde etmiştir. Eskizleri gerçekçi görüntülere dönüştürme, siyah beyaz görüntüleri renkli hale getirme, gündüz görüntülerini gece sahnelerine dönüştürme gibi görevlere başarıyla uygulanmıştır. Ayrıca, birçok farklı varyasyon ve genişletmeyi teşvik ederek, görüntü sentezi ve manipülasyonunda ilerlemelere yol açmıştır.

Pix2Pix GAN modeli daha sonra 1458 görüntüden oluşan bir veri kümesinde, Ortalama Mutlak Hata (MAE), Kök Ortalama Kare Hata (RMSE), Pik Sinyal-Gürültü Oranı (PSNR), Yapısal Benzerlik İndeksi Ölçümü (SSIM), Sinyal-Yeniden Oluşturma Hata Oranı (SRE), Spektral Açı Haritalayıcı (SAM) ve Evrensel Görüntü Kalite İndeksi (UIQ) gibi nicel ölçütler ve nitel bir inceleme ile değerlendirildi. Sonuçlar, modelin yüksek kaliteli görüntüler üretme konusunda etkili olduğunu gösterdi.

GAN eğitimi için en iyi modeli belirlemek ve aşırı uydurmaya engel olmak için veri kümesi üçe ayrıldı: eğitim, test ve doğrulama setleri. Tüm setler için en uygun dönem, görüntülerin görsel olarak incelenmesi, çeşitli nicel ölçütlerin ve görselleştirme yöntemlerinin karşılaştırılmasıyla belirlendi ve en iyi dönemin 30. dönem olduğu tespit edildi.

Bu çalışmanın sonuçları, pix2pix GAN modelinin yüksek kaliteli Zihinsel Sağlık Görüntüleri (MHI) oluşturmak için faydalı bir araç olduğunu ve bu görüntülerin değerli bilgileri tespit etmede yenilikçi kullanımlara sahip olabileceğini göstermektedir. Uzun anketler yerine görüntülerin kullanılmasıyla, İK işverenleri istenen bilgilere hızla ulaşabilir.

Ayrıca, bulgular, mülakatlarda potansiyel işverenlere zihinsel sağlık sorunlarını açıklayan bireyler, iş performansını etkileyen zihinsel sağlık koşulları ve aile geçmişi olan bireyler arasında önemli bir ilişki olduğunu ortaya koymaktadır. Bu sonuçlar, zihinsel sağlık sorunlarının iş verimliliğini veya performansını etkileyebileceğine inanan potansiyel çalışanlara yardımcı olmak için İK departmanlarına önerilen vizyoner hedefleri destekleyebilir.

pix2pix GAN'ın öngörü yeteneği, insan kaynakları profesyonelleri için değer taşımaktadır çünkü mevcut verilere dayanarak çalışanlarda mental sağlık durumlarını belirlemede veya tahmin etmede potansiyel olarak yardımcı olabilir. Bu araç, insan kaynakları profesyonelleri için karar verme sürecini kolaylaştırabilir ve erken müdahale veya hedefe yönelik destek sağlayarak çalışanların mental sağlığını geliştirmeye olanak tanır.

1. INTRODUCTION

In this day and age, mental illness is one of the most common health concerns in all parts of the world. Millions of people are suffering from Mental Health Disorder (MHD), which is also known as mental illness disorder with diverse symptoms ranging from feeling down and sad, excessive worries or fears, sleeping issues, low energy, and significant tiredness [1]. Over 350 million people suffer from depression, according to statistics published by the World Health Organization (WHO). As far as the economic impact is concerned, mental health problems cost the world approximately US $2.5 trillion in 2010. It is estimated that the costs will increase to US $6.0 trillion by 2030 [2]. In late June 2020, 40% of U.S. grown-ups reported battling with mental well-being or substance utilization. One out of six U.S. youth aged 6-17 experience a psychological wellness problem every year [3]. Accordingly, the number of people who are affected by mental health disorders such as anxiety, depression, and stress has increased with the development of the modern world [4].

Mental health issues are considered a prominent factor in the overall health and culture of a company including employees' satisfaction, productivity, efficiency, and performance [5], and the workplace was previously identified as a major contributor to an individual's mental well-being [6]. Well-being at work has been considered a crucial element for ensuring economic and commercial growth [7,8]. Recent studies found that work-related stressors, such as high job demands, occupational uncertainty, and effort-reward imbalance, are widely associated with an increased risk of developing common mental health issues, such as depression and anxiety [9]. Furthermore, many researchers have shown that workplace stress can lead to a decrease in the productivity of a company, increased turnover rates of employees, and diminished morale and burnout [10,11]. Recently a study led by – World Health Organization (WHO) estimated that mental health disorders cost the global economy US $ 1 trillion each year in lost productivity.

The World Health Organization (WHO) has noted that employers avoid providing mental health programs and services for their employees for a number of reasons [12]. The most prominent reason that employers fail to devise effective support systems to properly care for the mental health of their employees is due to misidentification of the factors leading to mental illnesses [5]. Moreover, people often feel uncomfortable opening up about mental illness – especially at work [3].

Studies have shown that work-related stress and employee mental health vary from occupation to the occupation [13,14]. Information Technology (IT) related jobs, which demand high tasks, tend to be associated with mental health issues. As a result of such workplace environments, mental stress has been exacerbated when external demands and expectations exceed the professional's capacity, skills, and knowledge to effectively deal with problem-solving and relevant tasks [15]–[17]. Furthermore, Experiencing such situations negatively impacts health outcomes (both physical and mental), such as depression, anxiety, emotional exhaustion, immune deficiency disorders, and cardiovascular diseases [18].

Nowadays, with the explosion of knowledge and the revolution of the information technology (IT) industry, Artificial Intelligence (AI) and Machine Learning (ML) have played an instrumental role in the mental health field, most especially in the prediction of mental disorders and the development of personalized healthcare plans [19]. Recently, AI-based solutions for Mental Health have started to be embedded in devices such as smartphones and wearable devices, providing live health risk assessments and symptom monitoring [20]. These tools and applications not only assist HR departments to acquire a deeper knowledge of their employees but also provide the opportunity for the administration to put in place preventative policies that will determine which types of therapy a person needs for their mental health at an early stage.

1.1 Motivation

The primary motivation of this study is to explore ways of identifying IT employees who are experiencing various types of mental disorders but choose to conceal their conditions due to personal preferences in the workplace. The aim is to provide assistance and support tailored to their needs.

Furthermore, a few years ago, the utilization of images for disease detection and precise analysis of human body details emerged as a promising approach in diagnosing illnesses. Presently, this method has evolved into a significant breakthrough in diagnostic methodologies. By visualizing data through images, healthcare professionals can leverage deep learning techniques to enhance the accuracy and efficiency of psychiatric disorder diagnoses. This serves as the motivation for this study - to introduce a more suitable approach in the workplace by converting raw data into comprehensive and informative images that can be quickly interpreted.

1.2 Objective and Research Challenges

This study aims to enhance our understanding of mental health by transforming patients' data into visual images. Compared to raw data, images offer a more compact and easily understandable representation, allowing for efficient communication and comprehension. As a result, meaningful images can convey more detailed and comprehensive information in a shorter amount of time. First and foremost, Previous studies on OSMI data have not explored the conversion of raw data to images and the analysis of the results. Therefore, this research introduces a novel approach that contributes to the emergence of Mental Health Images (MHI).

This research applies Deep Learning (DL) techniques, which have gained considerable attention in recent years due to their capability to extract meaningful features and representations directly from raw data. DL has already demonstrated successful applications in neuroimaging studies of psychiatric disorders. However, there exists a gap in the examination of OSMI (Open Sourcing Mental Illness) datasets, which provide valuable psychological data but have not been utilized as psycho-images in research investigations. Consequently, the objective of this research is to employ DL methods to generate enhanced and reliable mental health images, thereby investigating significant mental health concerns more effectively by creating MHI.

Furthermore, this thesis aid the human resources department in detecting mental illnesses among employees by using cutting-edge artificial intelligence tools and offering effective treatment. To achieve this, the study investigates the link between mental health and the workplace through survey questions. The findings are then used to create a novel model utilizing pix2pix GAN, which can be implemented as an optimal and pre-established tool across various departments. The generated model simplifies the assessment process, allowing HR to evaluate employees' mental health status using a selected set of questions instead of a lengthy questionnaire that is often ignored or answered imprecisely. By streamlining the process, the model not only helps HR identify healthy and qualified job candidates with the related tasks but also allows them to plan programs to support employees' mental health. This enhances workplace productivity, improves the company's performance, and ultimately contributes to the economic growth of the country.

The main focus of this thesis is:

How translating mental health OSMI data of employees into images and developing a Pix2Pix GAN model for Image-to-Image translation can enhance the accuracy of the information required by the human resources (HR) department in the workplace?

1.3 Approach and Methodology

Deep Learning (DL) has emerged as a powerful tool for analyzing complex and large-scale datasets in a variety of domains, including healthcare. Deep learning models are able to learn hierarchical representations of data that can capture complex relationships and dependencies within the data. This makes them well-suited for analyzing mental disorder data, which is often complex and multi-dimensional. Unlike traditional ML approaches, DL models can learn features directly from the raw data, eliminating the need for manual feature engineering.

Additionally, DL has been applied to a range of mental disorder data, including neuroimaging data, electronic health records, and social media data. These applications have shown promising results in the areas of diagnosis, prognosis, and treatment prediction. DL models have also been used to develop predictive models that can identify individuals at risk of developing mental disorders, allowing for early intervention and prevention.

Overall, Deep learning has the potential to discover the field of mental health by providing powerful tools for analyzing complex and diverse data, improving diagnostic accuracy, and enabling personalized treatment approaches. So, the pix2pix GAN model as a tool of deep learningp has been applied in the research study to satisfied the proposed model.

1.4 Thesis Outline

Chapter (1) of the study provides a brief overview of the research motivation, objective, and methodology. Chapter (2) reviews relevant literature on workplace mental disorders, OSMI data, and deep learning models to contextualize the forthcoming research within existing theoretical paradigms and identify areas for further investigation. Chapter (3) explains and justifies the research methodology, including data descriptions and collection, preprocessing, application and visualization. Chapter (4) presents the descriptive statistics, results of statistical analysis and discussion, followed by the conclusion, limitations, and future research directions in Chapter (5).

2. LITERATURE REVIEW

2.1 Workplace Mental Disorders

Workplace mental health encompasses more than merely the absence or presence of mental disorders; it also involves factors that promote mental well-being or motivational factors [21]. Mental health is defined by the WHO as a state of well-being in which every individual realizes their own potential, can cope with life's normal stresses, is capable of working productively and fruitfully, and contributes to the community they belong to [22].

Mental health is an increasingly important issue in the workplace due to the prevalence of mental health disorders, especially depression and anxiety, which are now considered the leading causes of sick leave, and long-term disability in most the developed countries [23]–[25]. It is a fundamental topic that has been considered and studied in recent years. Some studies have discussed the complex inter-relationship between mental health and work productivity in developed countries [26]. Mental disorders have led to reduced labour market activity, which means people with mental illness are less likely to work, and those who do work earn less than workers without mental illness [27].

Studies that have examined well-being and mental health in the workplace have found heterogeneity in the use of these terms [28]. A few studies have already tried to provide a systematic review of the literature on the relationship between interior office space and employees' well-being, but the terms used to describe the workplace were general, such as 'office', 'workplace design', or 'architecture' [29].

The effect of a physical workplace on the mental health of employees therefore depends on people's psychological and physiological reactions to the physical characteristics of the workplace [30]. As Sander et al. [31] found that the reactions of employees to the physical work environment can be evaluated by their cognitive, emotional, and relational responses to the whole office environment or to specific characteristics. These characteristics can be divided into resources (i.e. salutogenic) and demands (i.e. pathogenic), based on the way they might affect employees' mental health [32]. Previous research shows that the physical characteristics of the workplace (eg light, noise, air quality) can affect workers' mental health (eg stress, fatigue or mood) [29]. A person may experience mental disorders, which are diagnosable conditions by changes in thought, mood, or behavior (or a mix of these), which can make them feel anxious or make it difficult for them to function [33].

There are a different types of mental disorders:

2.1.1 Anxiety disorders

The most common class of mental diseases is anxiety disorders. They make up the largest subset of mental diseases and are extremely burdensome for both individuals and society. Many people with anxiety disorders visit their primary care doctors after developing physical symptoms associated with their condition. According to the Diagnostic and Statistical Manual of Mental Diseases, disorders with excessive fear and associated behavioral problems are included in the category of anxiety disorders. Generalized anxiety disorder, panic disorder, agoraphobia, social anxiety disorder, and post-traumatic stress disorder are the several types of anxiety disorders [34] .

2.1.2 Mood disorders

A mood disorder is a mental disease that seriously affects the way people feel and think. Unlike normal fluctuations, they are characterized by severely fluctuating emotional states [35]. The two most common mood disorders are depression and bipolar disorder. Around 5% of adults suffer from depression, characterized by sad or irritable moods with a lack of interest or pleasure in activities for most of the day, nearly every day, for at least two weeks [36].

Bipolar disorder (formerly known as manic-depressive disorder) results in dramatic shifts in moods, and energy that impact one's daily life by shifting between depressive moods and impulsive, high-energy moods. The latter category of mood is known as mania [37].

2.1.3 Psychotic disorders

It is common for people who suffering from psychotic disorders to experience functional impairments, decreased quality of life, persistent symptoms, substance abuse comorbidity, and frequent side effects of their medications. The majority of these people are living in severe social isolation and in adverse socioeconomic circumstances despite the high utilization of mental health services. The lack of community-based rehabilitation, supported housing, and employment opportunities stands out as particularly unmet needs [38].

2.1.4 Eating disorders

There are three distinct diagnostic entities within the Feeding and Eating Disorders: A person with anorexia nervosa fears gaining weight and restricts food; a person with bulimia nervosa binges, excessively exercises, and abuses laxatives; and a person with binge eating disorder, characterized by distress associated with eating large amounts of food in a short time frame [39]. It was noted by the National Eating Disorder Association that ED can negatively impact productivity at work, resulting in lower productivity for both diagnosed and undiagnosed workers [40]. Individuals with ED have also been found to have unemployment and social disability levels as high as those with schizophrenia and personality disorders [41,42].

2.1.5 Attention deficit hyperactivity disorders

The Diagnostic Statistics Manual of the American Psychiatric Association states that in order to identify someone with Attention Deficit Hyperactivity Disorders, "a persistent pattern of inattention and/or hyperactivity/impulsivity that interferes with functioning and development" must be seen [43].

Inattentive type, Hyperactive-Impulsive type, and Combined type are the three common forms of Attention Deficit Hyperactivity Disorders [44]. However, these sorts will vary depending on the distinct symptoms that a person may display and the type for which they are diagnosed. According to Harris [45], persons with Attention Deficit Hyperactivity Disorders symptoms may exhibit unwelcome behaviors that lead to job loss or social isolation. Attention Deficit Hyperactivity Disorders individuals face barriers to employment in every area of their lives, including finding a job, interviewing, and finding a job [46].

2.1.6 Personality disorders

Personality disorders, as defined by the American Psychiatric Association, 1980, represent extreme examples of tendencies observed in the general population. There is a close relationship between several of the standard personality disorders and symptom disorders (Schizophrenic, Delusional, Obsessive-Compulsive, Phobic, Violent Explosive, etc.) [47]. Five distinct forms of personality disorders (PDs) have been suggested by the Personality and Personality Disorders Work Group: antisocial/psychopathic, avoidant, borderline, obsessive-compulsive, and schizotypal. Each kind is recognized by shared symptomatic behaviors, disordered personality features, and basic personality functioning abnormalities [48].

2.1.7 Obsessive-compulsive disorders

Obsessive-compulsive disorder is a severe and disabling mental disorder that presents several challenges for neuroscience. Obsessive-compulsive illness includes disorders such as body dysmorphic disorder, hoarding disorder, trichotillomania, and excoriation disorder [49]. There are existing treatments for this chronic, costly, and disabling brain disorder, however, they produce disappointing results most of the time [50].

2.1.8 Post-traumatic stress disorders

According to the American Psychiatric Association, Post-Traumatic Stress Disorders is a mental disorder caused by experiencing or witnessing a traumatic event, such as a natural disaster, a serious accident, a terrorist act, war/combat, rape, or other violent personal assault [51]. A person with this disorder has recurrent thoughts about traumatic experiences that impact their daily lives. In general, there is a 12.5% lifetime prevalence of Post-Traumatic Stress Disorders. Despite this, Post-Traumatic Stress

Disorder is often misdiagnosed or left untreated, resulting in incorrect, incomplete, or missed treatment [52].

2.1.9 Stress response syndromes disorders

Stress-response syndrome consists of several signs and symptoms that appear after a serious event occurs or a life circumstance that poses a threat to one's well-being. Injury, assault, or loss of a loved one are the most common experiences observed as precipitants of stress disorders in clinical practice [53].

2.1.10 Dissociative disorders

In the 1800s, the French physician Pierre Janet [54,55] introduced the concept of dissociation to medicine when he described it as the breakdown of the integration of mental processes necessary for a unified experience of self and consciousness.

There are three dissociative disorders listed and defined:Dissociative Identity Disorder, Dissociative Amnesia, and Depersonalization/Derealization Disorder, as well as Other Specified Dissociative Disorder and Unspecified Dissociative Disorder. In the current theory of dissociation, a wide range of phenomena are considered, including highly pathological disturbances of memory, such as amnesia, and consciousness disturbances as well as identity disturbances, as well as benign and common experiences involving attention, such as daydreaming, fantasy, and absorption [56].

2.1.11 Substance use disorders

A substance use disorders involves abuse or dependence on illicit drugs like stimulants, opiates, and alcohol [57]. A person with substance use disorder who is professionally active or engaged in meaningful activity, as well as has a caring family, faces fewer challenges than one who lacks social support and is isolated [57]. Workplace problems related to substance use disorders have not been addressed systematically or appropriately. In most existing measures, workplace needs are prioritized over the perception of employees' difficulties both at work and in their personal lives. A workplace prevention policy that prevents and manages substance use disorders leads to a safer workplace, a more motivated workforce, and more productive workers [58].

2.1.12 Addictive disorders

A person with an addiction disorder is diagnosed based on self-reported symptoms and information about problematic behaviors [59]. For example, as a behavioral addiction, gambling disorder causes social problems including debt and unemployment because of the inability to stop gambling. According to the Diagnostic and Statistical Manual of Mental Disorders 5th Edition, gambling disorder is classified into two categories: Substance-related Disorders and Addictive Disorders [60].

As defined in the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders, mental illness encompasses more than 200 mental health disorders classified by the American Psychiatric Association. The Center for Disease Control and Prevention defines it as diagnosable psychological disorders that are characterized by dysregulation of mood, thought, and behavior. It is important to note that mental diseases vary in severity and continuity, and once a disorder is diagnosed, an individual may remain susceptible to it for the rest of their life [61]. To be more precise, Mental health can be defined as the capacity of the individual to cope with both internal needs and external needs, such as roles and responsibilities within employment [62].

Studies of employee well-being have been conducted for decades [63,64] with a focus on identifying the factors that influence employees' mental health and well-being [65,66]. The psychological health of employees is often characterized by the presence of effective states, such as depression [67] or anxiety [68], which can be momentary or normative in response to specific circumstances.

At workplaces, mental illnesses, and especially Common Mental Disorders (CMDs), including depression and anxiety, are among the most frequent causes of occupational disability [69]. Furthermore, there are various environmental factors; the political environment, policies that govern the labor market, access to basic services including health services, and stability of social and family networks, have an impact on the health of workers [70]. Fairness of workplace processes includes organizational justice, which refers to the fairness of workplace procedures,and Low organizational justice has been linked with an increased risk of CMDs [71]. The economic status of the nation, living conditions, access to adequate housing, and access to recreational pursuits, may all have an indirect impact on the workplace environment [72]. There is much evidence has shown that workplace interventions can be identified as an appropriate setting for primary care interventions to improve health and also hence in turn improve workplace productivity [73], which has led to economic and social sustainability, increasing employees' commitment, and decreasing labor turnover. Based on different occupations, the relationship between mental health and work has been investigated in terms of psychological outcomes. Clinically relevant psychological distress, depression, suicide rates, and drug and alcohol abuse are four outcomes that recently have received considerable research interest [74]. Most common mental health problems are treatable and in some cases preventable [75]. Despite this, depression and anxiety continue to impose significant economic, social and personal costs on workers, employers and society [76,77]. Given these rising costs, it is not surprising that many policy makers consider workplace mental health a major public health issue and seek advice on effective interventions.

2.2 Mental Disorders and Artificial Intelligence

A fundamental philosophical direction of artificial intelligence is augmenting people's intelligence with machines that are intelligent enough to solve problems better than humans alone, and that's what AI is all about. The emergence of Artificial Intelligence (AI) has sparked a revolution in the fields of pattern recognition and image analysis, offering immense possibilities for its use in medical image computing in various medical domains [78]. Medical diagnosis is difficult for humans, and it actually takes a lot of time without the help of intelligent machines. For diagnosis tasks, AIM (Artificial Intelligence in Medical) systems have been used in the healthcare system. Medical is the field where technology is much needed. When Artificial Intelligence was defined in the medical sciences in 1984, it was simply concerned with programs for analysis, treatment recommendations, and suggestions. Further, it is essential to know how it is verified that a computer program is equivalent to a human in terms of intelligence. As a solution to this issue, AI in medical sciences has been tested with the help of turning tests, which declared a given program as intelligent if the results were positive in more than 50 % of cases. The next thing that came up was what are the fields in which AI in medical sciences was first used and how it reached a high level in the medical sciences field as we look to [79].

In healthcare, AI is widely used, including to facilitate early disease detection, enable a better understanding of disease progression, optimize medication/treatment dosages, and uncover novel treatments [80]–[84]. Moreover, artificial intelligence is a package of techniques, which has the potential to redefine practitioners' diagnosis and understanding of mental illnesses [19]. Thus, AI can be used to develop better prediagnosis screens and formulate risk models to determine an individual's risk of developing mental illness [85].

AI has emerged in recent decades in areas such as medicine, human biology, and health care. Studies have been conducted on intelligent devices and instruments that aid in the medical field. There is a new branch of engineering known as medical knowledge engineering, and the main concept on which AI is working is the power of decision-making and detection through algorithms and huge available data [82]. The idea of modern technologies is to combine deep learning with AI in order to do classification, detection, segmentation, and other various medical predictions.

2.3 Machine Learning Models Used for Analysis of Mental Disorders

The study of data science has evolved as a means of dealing with the expanding volume of data and the analytical and computing resources it needs. In this new environment, machine learning techniques that enable researchers to extract information from large datasets have been repurposed and utilized to interpret data and build prediction models in a variety of fields, including finance [86], economics [87], politics [88], and crime [89]. With the use of data science techniques, researchers in the field of medical have been able to analyze vast healthcare datasets for patterns and useful information [90,91].

Machine learning is an a subset of artificial intelligrnce that has been emerged to analyze metadata in the mental health field. ML involves the use of advanced statistical and probabilistic techniques to construct systems with an ability to automatically learn from data enabling an algorithm to learn [19,92]–[94]. Therefore, access to patterns in big data-sets is faster, and prediction based on ML techniques is more accurate [95]. Within health fields such as bio-informatics, ML has led to significant advances by enabling speedy and scalable analysis of complex data [96]. Supervised, unsupervised, and deep learning are the most common styles of learning that are used pervasively for healthcare purposes [19,83,97].

Several papers have described their particular experiments with machine learning for mental health in recent academic literature. Bzdok and Lindenberg [19] reported machine learning's potential for a psychiatric diagnosis of Mental Health diseases instead of classical statistical methods.

According to Mohr et al. [98], data collected from a patient's daily life is used to develop a predictive model by examining their behavior, feelings, traits, and other characteristics generated by sensors in smartphones, wearable devices, and other devices for providing detailed work on mobile health interventions. Shatte et al. [92] synthesize the literature related to mental health research. They analyzed that the most popular research domains are detection and diagnosis, treatment and support, and research and clinical administration. Srividya et al. [99] proposed a machine learning model to investigate the relationship between factors like stress levels, disorders, and productivity at work. Jeong et al. [100] applied a Markov Decision Process model to learn about users' preferences for positive psychology interventions over time. Garlapati et al. [101] implement ML algorithms to predict employer stress levels during the Covid-19 Pandemic and the associated modified working conditions.

2.4 Deep Learning Models Used for Analysis of Mental Disorders

As a part of AI, deep learning (DL) has been a dominant force in many vision tasks such as detection, semantic segmentation, and image-to-image translation. In recent years, DL medical systems have gained widespread interest and been employed across diverse areas of medicine, from drug identification to medical decision-making, leading to a significant shift in the practice of medicine [102]. The algorithm's architecture is typically designed to mimic the neural layers of the human brain, enabling machines to learn without explicit programming. Trained models can be used for disease diagnosis, detecting risk factors such as Alzheimer's, breast cancer, retinal diseases, and more. Deep learning (DL), which transforms data through layers of nonlinear computing components, provides a novel paradigm for gaining meaningful knowledge from complex mental health data, being one of the latest advances in AI and ML [97]. In recent years, DL algorithms have shown excellent performance in many data-rich applications, including healthcare [83,103].

Durstewitz et al. [104] explored the emerging area of application of DL techniques in psychiatry. Based on their research on brain dynamics and subjects' behaviors, they presented insights on how to embed interpretable computational models into a statistical context.

Generative adversarial networks (GANs), which was introduced by Ian J. Goodfellow and his team [105] in 2014, is a new approach to generative modeling that uses a flexible unsupervised deep learning architecture, and are now a widely-used deep learning approach in computer vision for examining multimodal medical imaging data. GANs can generate realistic medical images and annotations, which can be used for image augmentation, registration, reconstruction, and translation. This has led to a rapid uptake of GANs in various medical image analysis applications. The various frameworks of GANs that have gained popularity in interpreting medical images, such as DCGAN, LAPGAN, Pix2Pix, CycleGAN, and UNIT, have been suggested, along with their continued performance improvements through additional hybrid architecture [106]. Numerous reviews have been published that describe and summarize the concepts, methods, algorithms, and various applications of GANs. In the medical field, Yi et al. [107] conducted a comprehensive review of recent GAN methods used in medical imaging analysis, with an extensive evaluation of results and application categorization. Kazeminia et al. [108] also explored the use of GANs for medical image analysis, covering tasks such as synthesis, segmentation, reconstruction, detection, and more.

GANs have found diverse applications in various fields, including but not limited to generating images based on textual input [109], creating realistic human face photographs [110], generating anime characters [111], and improving the resolution of images [112]. Wiatrak et al. [113] provided an overview of GAN training stabilization methods and categorized the problems in GAN training. Pan et al. [114] summarized the different types of GANs and their applications in various fields such as natural language processing, super-resolution, and image translation. Saxena et al. [115] addressed the instability issues in GANs training and proposed solutions by changing the architecture, loss function, or optimization method. Gui et al. [116] conducted a comprehensive survey of GAN models, including algorithms, theories, and applications. One particular area about interest of GAN methods is Image to Image Translation, where the goal is to learn a mapping between images from a source domain to a target domain, or even vice versa. Isola et al. [117] introduced Pix2pix as a successful version of cGAN [118] for image-to-image translation that requires an input and a desired output image. Pix2pix method has been used for image reconstruction [119], cross-modality [120], and data augmentation [121]. Yu et al. [122] conducted an empirical study that showed the superiority of the Pix2Pix network with a ResU-Net generator over other GAN methods based on single landmarks, regardless of their architectures. This was achieved by using high-resolution paired images and multiple-channels-multiple-landmarks. In addition, they were able to produce realistic and meaningful images.

2.5 Open Source Mental Illness Literature(OSMI)

The dataset for this study is obtained from Open Sourcing Mental Illness (OSMI). Open Sourcing Mental Illness [123] is a non-profit organization that aims to promote awareness of mental illness, and workplace disorders, and end the stigma surrounding distracted employees. One critical function of OSMI is helping workplaces in the identification of the most appropriate resources to help their employees overcome mental health issues. The OSMI mental health dataset is accessible to the public, and numerous studies have been conducted using this valuable information. OSMI Mental Health in Tech survey was used by Elmunsyah et al. [124] to determine the correlation between work and mental illness, as well as whether treatment should be sought immediately. The purpose of Katarya's paper [125] on open sourcing mental health 2019 was to determine which factors contribute to the development of mental health disorders among employees. Therefore, seven attributes were selected using feature selection, emphasizing medical and hereditary factors. Based on the results of several experiments, a Decision Tree was found to be the most accurate and precise model, with 84% accuracy and 83% precision. An interesting finding from feature importance is that having a family history of mental health disorders is the most significant contributor to the likelihood of developing a mental health disorder. Furthermore, On the tech survey dataset (OSMI), Mallick et al. [126] applied machine learning algorithms including SVM, Naive Bayesian Decision Tree, KNN and Logistic Regression to determine the percentage of technical people who suffer from mental illness disease compared to non-technical people. They concluded that SVM, KNN, and Logistic Regression algorithms provided better accuracy than other classification algorithms.

In a study by Reddy et al. [127], machine learning algorithms were used to analyze stress levels among workers at a company. Boosting methods, such as ensemble learning, resulted in better performance than other algorithms; It predicts stress and mental illness more accurately than other models with 75% accuracy.

To find the factors that affect mental health among employees, Sujal BH et al. [8] applied OSMI data. Different types of ML algorithms were used, and XG Boost provided better performance based on Precision, Recall, F1 Score, and Accuracy. Further, the results revealed that those who work in non-tech companies have more mental problems than those who work in tech companies, as well as those who live in cities.

In their study, Laijawala et al. [128] used data from OSMI that is available online and consists of survey-based information about working individuals. By using machine learning algorithms, they have developed a model that informs employees about their mental health and the need for immediate treatment. Elizabeth Oluyemisi Ogunseye et al. [129] used OSMI 2014 and 2016 datasets to discover how mental disorders were being diagnosed by using different types of supervised ML algorithms, which AdaBoost was shown to be the most successful tool among others. Moreover, the results showed that mental health frequently interferes with the performance of employees .

Saranya et al. [130] designed a model to discuss performance analysis of mental illness disorder detection using the proposed Chicken Swam Intelligence Enhanced Multilayer Perceptron (CSI-MLP) on OSMI 2019 dataset. It was observed that the proposed CSI-MLP, which overcomes overfitting problems by using lasso regression and removing attributes that do not contribute to predicting mental illness, produced higher accuracy compared to the other three conventional models . Appiah et al. [5] conducted a research on OSMI data to identify the factors that are most likely to predict an individual's likelihood to seek treatment. They used PCA for reducing the dimension of the survey dataset, and then applied DBSCAN (density-based spatial clustering of applications with noise) for clustering datasets into similar results. They concluded that among ML classification algorithms, the SVM classification with variables PCA component reached the higher accuracy than the Naive Bayesian algorithm.

3. METHODOLOGY

This thesis applies the Knowledge Discovery in Databases approach, which was previously proposed by Fayyad et al. [131] (1996). The primary goal of this approach is to gain knowledge about mental illness by processing, experimenting, evaluating, and eventually gaining insights. In part, the difficulty of KDD is due to the type and process of the data being analyzed. In summary, this technique involves selecting and exploring data, preparing it, transforming it, and implementing it. This methodology, which starts with data collection, extraction, and processing, is the best fit for this dataset. During the second stage of the application, the pix2pix GAN is utilized to produce and forecast mental health images associated with the OSMI dataset.

3.1 Knowledge Discovery in Databases

In the database process, knowledge discovery is the process of identifying useful information from data. In spite of the fact that there are numerous definitions of the KDD process [131]–[133], they all agree on its essential components. According to Fayyad et al. [131], KDD is an interactive and iterative process. There are nine main steps outlined by them:

- Determine the objective of the process and gather prior needed knowledge of the application domain.
- Choose a data set that is appropriate for extracting knowledge from.
- Preprocess the data that there are many things to consider in this process. The data set is cleaned up by removing noise and harmful records and setting certain settings, such as how missing attribute values are handled.
- Reduce the data to a form that can be represented, by removing variables or parameters that are not helpful to the task's objectives.

- Make a decision regarding the data mining approach for the KDD process based on the objectives defined.

- It is then necessary to choose the data mining algorithm once a general data mining approach has been chosen. It is important to note that the choice is often determined by the end user's preference, such as whether an understandable format is preferred or the maximum level of prediction accuracy.

- The main step in data mining is this one. It consists of applying an algorithm to a pre-processed data set. The algorithm then searches the data for valuable information.

- Review the patterns found by the algorithm and possibly return to a previous step to readjust the KDD process setup.

- The last step of the knowledge discovery process in databases involves interpreting the results for further actions, like applying a model to real-world situations or further research.

Iterations and loops can be part of the KDD process, as mentioned in step 8. For example, depending on how the results of the algorithm are interpreted, one might decide that the algorithm was chosen incorrectly and return to step 5, or after reducing the data in step 4, that the preprocessing has been done incorrectly and return to step 3 [134].

3.1.1 Dataset description and selection

This thesis utilizes data from Open Sourcing Mental Illness (OSMI), a non-profit organization that conducted the largest survey of mental health within the tech industry to raise awareness of mental illness and disorders in the workplace and to eradicate the stigma associated with such conditions. Furthermore, they offer workplace guidance on how to identify the most appropriate resources for this purpose [123].

Over 1484 responses were collected via Google Forms during 2017, 2018, 2020, and 2021, contributing to the dataset scoring very highly in access and provision. OSMI has made the raw data accessible on its website due to its digital format, and the data is licensed under a Creative Commons Attribution license, allowing free adaptation and sharing of the survey results. As the study is repeated every year between 2014 and 2021, the data provides opportunities to study trends over 8 years.

Understanding the characteristics of the questions answered in the data was crucial to the thesis. Therefore, it was necessary to analyze the various attributes, and this was achieved by closely examining the content. There are several questions in the survey, some of which are general (Age, Gender, Country, City, race, and so on), some of which are workplace-related (benefits, supervisor, employer, coworker and etc.) and some of which are personal (family history of mental illness).

Data quality information is limited, but the dataset is supported by extensive documentation. It would have been helpful if they had provided information about the type of tech companies where participants worked – this could have allowed us to compare attitudes toward mental health among healthcare tech firms versus financial tech firms, for example [123]. The Mental Health Tech Survey contains the following useful and psychometric variables that have been mentioned in the table (3.1). In the following of the thesis, this variables has been classified into two categories, which is explained later.

The data was presented in '.csv' format and seemed to have some problems with some attributes. A special character appears in the questions ("?", "strong", "/strong", "em", "/em", "*"), which was cleaned up before starting the pre-processing and analysis of the dataset. As it can be seen, a subset of questions from the OSMI Mental Health in Tech survey were answered in this dataset by multiple people working in the technology industry across multiple countries. Most of the responses came from the United States, United Kingdom, and Canada, while the rest came from 45 different countries. The data for this survey's subset was collected in 2017, 2018, 2020, and 2021, and 83 common attributes has been considered between these years.

This dataset was selected because it contains a variety and comprehensive set of questions about the mental health of respondents, the demographics of respondents, and how employers perceive mental health in the workplace.

Mental Health in Tech survey (OSMI dataset) defined two explanatory definition before starting the survey, which has been emphasized in the process of analyzing.

- A mental health disorder is defined as a mental illness that has been diagnosed by a doctor.
- A mental health issue is defined as a potential mental illness, which may or may not have been diagnosed by a doctor.

All questions that have been regarded as variables in this study are extensively described in the following table (3.1). It should be highlighted that all 12 distinct types of disorders are inquired about, spanning from the past to the present. This inclusive variables encompasses the subcategories of "Do you currently have a mental health disorder?" and "Have you ever been diagnosed with a mental health disorder?". These questions are repeated to determine if the individual is currently affected by a disorder or has been affected in the past.

3.1.2 Data exploration

The idea of data exploration is to efficiently extract information from data regardless of whether we know what are looking for or not. Visualizations are an easy method for studying and comprehending data. Visually examining the data will help to understand the structure of the data, how the numbers are distributed, and whether there are links in the dataset.

Table 3.1 : Mental Health Tech Survey Variables.

Variable	Question
V1	Are you self-employed?
V2	Are you self-employed?
V3	How many employees does your company or organization have?
V4	Is your employer primarily a tech company/organization?
V5	Is your primary role within your company related to tech/IT?
V6	Do you know the options for mental health care available under your employer-provided health coverage?
V7	Has your employer ever formally discussed mental health (for example, as part of a wellness campaign or other official communication)?
V8	Does your employer offer resources to learn more about mental health disorders and options for seeking help?
V9	Is your anonymity protected if you choose to take advantage of mental health or substance abuse treatment resources provided by your employer?
V10	If a mental health issue prompted you to request a medical leave from work, how easy or difficult would it be to ask for that leave?
V11	Overall, how much importance does your employer place on physical health?
V12	Overall, how much importance does your employer place on mental health?
V13	Do you have medical coverage (private insurance or state-provided) that includes treatment of mental health disorders?
V14	Do you know local or online resources to seek help for a mental health issue?
V15	Do you have previous employers?
V16	Was your employer primarily a tech company/organization?
V17	Have your previous employers provided mental health benefits?
V18	Were you aware of the options for mental health care provided by your previous employers?
V19	Did your previous employers ever formally discuss mental health (as part of a wellness campaign or other official communication)?
V20	Did your previous employers provide resources to learn more about mental health disorders and how to seek help?
V21	Was your anonymity protected if you chose to take advantage of mental health or substance abuse treatment resources with previous employers?
V22	Would you have felt more comfortable talking to your previous employer about your physical health or your mental health?
V23	Did you ever discuss your mental health with a previous coworker(s)?
V24	Did you ever have a previous coworker discuss their or another coworker's mental health with you?
V25	Overall, how much importance did your previous employer place on physical health?
V26	Overall, how much importance did your previous employer place on mental health?

Table 3.1 (continued): Mental Health Tech Survey Variables.

Variable	Question
V27	Do you currently have a mental health disorder?
V28	Have you ever been diagnosed with a mental health disorder?
V29	Anxiety Disorder (Generalized, Social, Phobia, etc)
V30	Mood Disorder (Depression, Bipolar Disorder, etc)
V31	Psychotic Disorder (Schizophrenia, Schizoaffective, etc)
V32	Eating Disorder (Anorexia, Bulimia, etc)
V33	Attention Deficit Hyperactivity Disorder
V34	Personality Disorder (Borderline, Antisocial, Paranoid, etc)
V35	Obsessive-Compulsive Disorder
V36	Post-traumatic Stress Disorder
V37	Stress Response Syndromes
V38	Dissociative Disorder
V39	Substance Use Disorder
V40	Addictive Disorder
V41	Have you had a mental health disorder in the past?
V42	Do you have a family history of mental illness?
V43	Have you observed or experienced an unsupportive or badly handled response to a mental health issue in your current or previous workplace?
V44	What is your age?
V45	What is your gender?
V46	What country do you live in?
V47	What is your race?
V48	What country do you work in?
V49	Would you feel more comfortable talking to your coworkers about your physical health or your mental health?
V50	Would you feel comfortable discussing a mental health issue with your direct supervisor(s)?
V51	Have you ever discussed your mental health with your employer?
V52	Would you feel comfortable discussing a mental health issue with your coworkers?
V53	Have you ever discussed your mental health with coworkers?
V54	Have you ever had a coworker discuss their or another coworker's mental health with you?
V55	If you have been diagnosed or treated for a mental health disorder, do you ever reveal this to clients or business contacts?
V56	If you have revealed a mental health disorder to a client or business contact, how has this affected you or the relationship?
V57	If you have been diagnosed or treated for a mental health disorder, do you ever reveal this to coworkers or employees?
V58	If you have revealed a mental health disorder to a coworker or employee, how has this impacted you or the relationship?
V59	Do you believe your productivity is ever affected by a mental health issue?

Table 3.1 (continued) : Mental Health Tech Survey Variables.

Variable	Question
V60	If yes, what percentage of your work time (time performing primary or secondary job functions) is affected by a mental health issue?
V61	Would you have been willing to discuss your mental health with your direct supervisor(s)?
V62	Did you ever discuss your mental health with your previous employer?
V63	Would you have been willing to discuss your mental health with your coworkers or previouse mployees?
V64	Have you ever sought treatment for a mental health disorder from a mental health professional?
V65	If you have a mental health disorder, how often do you feel that it interferes with your work when being treated effectively?
V66	Have your observations of how another individual who discussed a mental health issue made you less likely to reveal a mental health issue yourself in your current workplace?
V67	How willing would you be to share with friends and family that you have a mental illness?
V68	Would you bring up your mental health with a potential employer in an interview?
V69	Are you openly identified at work as a person with a mental health issue?
V70	Has being identified as a person with a mental health issue affected your career?
V71	How has it affected your career?
V72	Overall, how well do you think the tech industry supports employees with mental health issues?

The dataset file format is in CSV format in the figure (3.1), so it was not necessary to make any changes to it. The models were implemented using the same file. As it is obvious from raw data, Most variables in the dataset are string types, which must be converted to a boolean data type . Then, the dataset has been checking for null (N/A) or missing values. Upon identifying the type of each variable, the finding reveals that there are some null values in the dataset, which should be scaled to be significant data for the employment of the proposed model.

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	
0	0	100-500	1.0	1.0	Yes	No	I don't know	I don't know	I don't know	Same level of comfort for each	Yes	0.0	Yes	1.0	1.0	6.0	0.0		
1	0	100-500	1.0	1.0	Yes	No	No	I don't know	I don't know	Same level of comfort for each	Maybe	0.0	Yes	1.0	1.0	7.0	2.0		
2	0	6-25	1.0	1.0	No	I don't know	No	Yes	Difficult	Same level of comfort for each	Yes	1.0	Maybe	1.0	0.0	0.0	1.0		
3	0	More than 1000	1.0	1.0	Yes	I don't know	I don't know	Yes	Difficult	Same level of comfort for each	Yes	1.0	Yes	1.0	0.0	7.0	5.0		
4	1																	0.0	Yes,
5	0	100-500	1.0	0.0	No	No	I don't know	Yes	Somewhat easy	Physical health	Maybe	0.0	Maybe	0.0	0.0	9.0	5.0		
6	0	6-25	1.0	1.0	Yes	No	No	Yes	Very easy	Same level of comfort for each	Yes	0.0	No	1.0	1.0	10.0	10.0		
7	0	26-100	1.0	1.0	No	No	No	I don't know	Somewhat easy	Physical health	Yes	0.0	Maybe	0.0	1.0	10.0	8.0		
8	0	100-500	0.0	1.0	No	No	No	Yes	Very easy	Same level of comfort for each	Maybe	0.0	Maybe	0.0	0.0	9.0	7.0		
9	1																	1.0	No,
10	0	100-500	0.0	1.0	Yes	No	No	I don't know	I don't know	Physical health	No	1.0	No	1.0	1.0	1.0	0.0		
11	0	100-500	1.0	1.0	No	No	I don't know	I don't know	Difficult	Physical health	Maybe	0.0	No	0.0	0.0	5.0	3.0		
12	0	More than 1000	1.0	1.0	No	No	No	I don't know	Neither easy nor difficult	Same level of comfort for each	Maybe	1.0	Yes	1.0	1.0	7.0	7.0		
13	0	More than 1000	1.0	1.0	No	No	I don't know	I don't know	Neither easy nor difficult	Physical health	Maybe	0.0	Maybe	0.0	0.0	3.0	2.0		
14	0	26-100	1.0	0.0		I don't know	I don't know	Yes	Very easy	Same level of comfort for each	Maybe	1.0	Yes	1.0	1.0	5.0	5.0		
15	0	100-500	0.0	1.0	No	No	I don't know	I don't know	Somewhat easy	Physical health	Yes	0.0	Maybe	0.0	0.0	8.0	3.0		
16	0	26-100	0.0	1.0	No	No	No	Yes	Neither easy nor difficult	Same level of comfort for each	Yes	0.0	Yes	1.0	1.0	9.0	9.0		
17	1																	1.0	No,
18	0	6-25	1.0	1.0	No	No	No	I don't know	Somewhat easy	Physical health	Maybe	0.0	Maybe	1.0	0.0	4.0	3.0		
19	0	More than 1000	0.0	1.0	No	No	I don't know	I don't know	Neither easy nor difficult	Physical health	Maybe	0.0	Maybe	0.0	1.0	4.0	3.0		
20	0	6-25	1.0	1.0	No	No	No	I don't know	Neither easy nor difficult	Physical health	No	0.0	No	0.0	1.0	2.0	2.0		
21	0	100-500	0.0	0.0		Yes	Yes	Yes	Somewhat difficult	Physical health	Yes	0.0	Yes	1.0	0.0	7.0	7.0		
22	0	26-100	0.0	1.0	No	No	No	I don't know	Difficult	Physical health	Yes	1.0	Yes	1.0	1.0	8.0	2.0		
23	0	1-5	1.0	1.0		No	No	I don't know	Difficult	Mental health	Maybe	1.0	Maybe	1.0	1.0	6.0	7.0		
24	0	100-500	1.0	1.0	No	Yes	No	I don't know	I don't know	Physical health	No	0.0	Maybe	0.0	0.0	10.0	5.0		
25	0	6-25	1.0	1.0	No	No	No	Yes	Very easy	Same level of comfort for each	Yes	0.0	Maybe	0.0	0.0	7.0	0.0		

Figure 3.1 : Raw Dataset.

3.1.3 Data pre-processing and transformation

The most essential processes in data preparation include splitting the data into train and test, removing missing data, categorizing values, and normalizing them.

When dealing with large data sets, the presence of special characters, missing values, and blank spaces can impact the performance of the proposed model. These characters should be treated with care in order to preserve and not manipulate the essential information during the preparation process. Despite the consistency of the data source, there were some issues with data consistency across all years.

OSMI points out some of these issues to mitigate the issues to make the visualizations as accurate as possible. The datatype of the file was string, which was converted to the range of number between [-1,1]. The presence of missing values is problematic for the model and could impede its performance. There are some missing values in each row and column of the dataset that indicate questions that were not answered by the respondent. Thankfully, the variables we are considering are filled out by the majority of users, and so we are not dealing with a severe missing values problem. For example, when a column is completely missing, the column is ignored as a whole.

This thesis implemented a large dataset with 1484 users, and the scale and the distribution of the data drawn from the domain are different for each variable. When input variables differ in scale, the problem may be more difficult to model. Large input values (e.g. a spread of hundreds or thousands of units) can result in a model learning large weight values. Models with large weight values are often unstable, resulting in poor performance during learning and high sensitivity to input values.

Despite many data distribution tools being introduced as Gaussian or uniform distributions in other studies, this study performed differently. In order to explain this in such a different way, there are two reasons:

First, it is possible to represent an image as a set of numerical values for its pixels. In the case of a (256x256) grayscale image, this vector can be represented by 65536 integers (bytes) between 0 and 255. An image based on such a randomly sampled vector will most likely appear as noise. The reason is that pixels in this dataset are not uniformly random, but they do have some structure. Consequently, an image domain's distribution refers to the distribution of pixel values which follows . This applies to grayscale images as well as color images in RGB.

Second, due to the fact that the aim of this research in preprocessing data is to convert it into a picture, the novelty is to scale all data in the range [-1,1] to satisfied the requirement of algorithm in the proposed pix-2-pix GAN model and to use the Tanh activation function for GAN generator output layers.

To preprocess and pre-analyze data, the Panda library has been used. The steps involved in preprocessing are as follows:

- Questions like self-employed with two binary answers and no null responses, the columns scale to No = -1 and Yes = 1.
- Questions like employee numbers, which are ordinal variables [1-5, 6-25, 26-100, 101-500, 500-1000, and more than 1000] were transformed into a scaled range between [-1,1], and the ordinal measures are coded by the increment of values between [-1,1] with the lowest value of the range is divided by 6, which yields a range of 7 with a "nan".
- Questions with [Y, N, N/A] , [Y, N, Maybe], [Y, N, nan] are coded as [1,0,-1]
- Responses with [I don't know], [Not applicable to me] has been equated with [nan] responses to some questions as employer has ever discussed MH, or whether you reveal MD to coworkers/employers..
- Physical health is coded as [-1] and Mental Health as [1].
- Age years have been classified into three groups: [Group1 = 18-35 years , Group2 = 35-50 years, Group3 = 50-70 years]
- Gender has many bad data, which consisted of incomplete, inconsistent, and inaccurate information such as [femalw, Woman, femail, female (cis), Woman-identified, to mention but a few], same as for men, and all grouped in female and was coded to indicate females equal to [1] and males equal to [zero].
- Living countries have been classified into [Group1 (Developed Countries), which is Group of Seven (G7) including United Kingdom, United States of America, Germany, Canada, Japan, Italy, France] is coded as [1], [Group2 (Developing Countries) , which is Group of Twenty (G20) including Argentina, India, Australia, Mexico, Turkey, Russia, China, Indonesia, Brazil, South Africa, EU: (Slovenia, Belgium, Croatia, Czech Republic, Finland, Portugal, Estonia, Greece, Hungary, Bulgaria, Ireland, Argentina, Latvia, Netherlands, Poland, Romania, Slovakia, Spain, Sweden)] is coded as [0], and [Group3 consists of others as Bangladesh, Israel, Iceland, and so on.], which is coded as [-1].

- There are some options about races [White, American Indian or Alaska Native, Black or African American, I prefer not to answer, More than one of the above, and Asian], which was coded as previous step between [-1,1].

- About working Countries, there are some people who live in and work in different countries as remote working, which was categorized as living countries step.

- In regards to the current types of twelve disorders and disorders that a worker has from the past to the present, the string data is coded as disorder type [Anxiety disorder = 1] equal to [1] and otherwise [-1].

As part of the data processing step, some people are identified who did not prefer to say what they experienced correctly about their disorders, i.e., they replied to a question about their current disorder and said no disorder they experienced in the past and present. The data should be cleared of these incorrect answers in order to catch accurate and precise data for applying the selected algorithm and reaching the best performance possible. Therefore, the cleaned dataset consists of 1458 users.

Regarding individuals who did not respond to questions about their diagnosed disorders, this analysis identified 61 individuals who reported being cured over time. They indicated that they do not currently experience any mental disorders, although they had previously experienced them in past years, which can be verified as evidence of their recovery. Here is a fragment of the scaled dataset that has been presented in the figure (3.2):

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
0	-1.0	0.33333333333333326	1.0	1.0	1.0	-1.0	0.0	0.0	-0.33333333333333337	-0.33333333333333337	1.0	-1.0	1.0	1.0	1.0
1	-1.0	0.33333333333333326	1.0	1.0	1.0	-1.0	-1.0	0.0	-0.33333333333333337	-0.33333333333333337	-0.33333333333333337	-1.0	1.0	1.0	1.0
2	-1.0	-0.6666666666666667	1.0	1.0	-1.0	0.0	-1.0	1.0	-1.0	-0.33333333333333337	1.0	1.0	-0.33333333333333337	1.0	-1.0
3	-1.0	1.0	1.0	1.0	1.0	0.0	0.0	1.0	-1.0	-0.33333333333333337	1.0	1.0	1.0	1.0	-1.0
4	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.33333333333333326	0.33333333333333326	0.0	0.33333333333333326	0.0	0.0
5	-1.0	0.33333333333333326	1.0	-1.0	-1.0	-1.0	0.0	1.0	0.6666666666666667	-1.0	-0.33333333333333337	-1.0	-0.33333333333333337	-1.0	-1.0
6	-1.0	-0.6666666666666667	1.0	1.0	1.0	-1.0	-1.0	1.0	1.0	-0.33333333333333337	1.0	-1.0	-1.0	1.0	1.0
7	-1.0	-0.33333333333333337	1.0	1.0	-1.0	-1.0	-1.0	0.0	0.6666666666666667	-1.0	1.0	-1.0	-0.33333333333333337	-1.0	1.0
8	-1.0	0.33333333333333326	-1.0	1.0	-1.0	-1.0	-1.0	1.0	1.0	-0.33333333333333337	-0.33333333333333337	-1.0	-0.33333333333333337	-1.0	-1.0
9	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.33333333333333326	0.33333333333333326	0.0	0.33333333333333326	0.0	0.0
10	-1.0	0.33333333333333326	-1.0	1.0	1.0	-1.0	-1.0	0.0	-0.33333333333333337	-1.0	-1.0	1.0	-1.0	1.0	1.0
11	-1.0	0.33333333333333326	1.0	1.0	-1.0	-1.0	0.0	0.0	-1.0	-1.0	-0.33333333333333337	-1.0	-1.0	-1.0	-1.0
12	-1.0	1.0	1.0	1.0	-1.0	-1.0	-1.0	0.0	0.33333333333333326	-0.33333333333333337	-0.33333333333333337	1.0	1.0	1.0	1.0
13	-1.0	-0.33333333333333337	1.0	-1.0	0.0	0.0	0.0	1.0	1.0	-0.33333333333333337	-0.33333333333333337	1.0	1.0	1.0	1.0
14	-1.0	0.33333333333333326	-1.0	1.0	-1.0	-1.0	0.0	0.0	0.6666666666666667	-1.0	1.0	-1.0	-0.33333333333333337	-1.0	-1.0
15	-1.0	-0.33333333333333337	-1.0	1.0	-1.0	-1.0	-1.0	1.0	0.33333333333333326	-0.33333333333333337	1.0	-1.0	1.0	1.0	1.0
16	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.33333333333333326	0.33333333333333326	0.0	0.33333333333333326	0.0	0.0
17	-1.0	-0.6666666666666667	1.0	1.0	-1.0	-1.0	-1.0	0.0	0.6666666666666667	-1.0	-0.33333333333333337	-1.0	-0.33333333333333337	1.0	-1.0
18	-1.0	1.0	-1.0	1.0	-1.0	-1.0	0.0	0.0	0.33333333333333326	-1.0	-0.33333333333333337	-1.0	-0.33333333333333337	-1.0	1.0
19	-1.0	-0.6666666666666667	1.0	1.0	-1.0	-1.0	-1.0	0.0	0.33333333333333326	-1.0	-1.0	-1.0	-1.0	-1.0	1.0
20	-1.0	0.33333333333333326	-1.0	-1.0	0.0	1.0	1.0	1.0	-0.6666666666666667	-1.0	1.0	-1.0	1.0	1.0	-1.0
21	-1.0	-0.33333333333333337	-1.0	1.0	-1.0	-1.0	-1.0	0.0	-1.0	-1.0	1.0	1.0	1.0	1.0	1.0
22	-1.0	-1.0	1.0	1.0	0.0	-1.0	-1.0	0.0	-1.0	1.0	-0.33333333333333337	1.0	-0.33333333333333337	1.0	1.0
23	-1.0	0.33333333333333326	1.0	1.0	-1.0	1.0	-1.0	0.0	-0.33333333333333337	-1.0	-1.0	-1.0	-0.33333333333333337	-1.0	-1.0
24	-1.0	-0.6666666666666667	1.0	1.0	-1.0	-1.0	-1.0	1.0	1.0	-0.33333333333333337	1.0	-1.0	-0.33333333333333337	-1.0	-1.0
25	-1.0	1.0	-1.0	1.0	-1.0	-1.0	0.0	0.0	-0.6666666666666667	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0

Figure 3.2 : Scaled Dataset.

3.1.4 OSMI data visualization

Data visualization is a technique that represents data in a way that is easy to understand and present by providing graphs, charts, and other visual aids. So, this approach helps to make complex data more accessible and understandable. In this thesis, Python libraries such as Matplotlib, Plotly, and Seaborn are used to achieve this goal.

Matplotlib is a widely used data visualization library in the Python programming language and is used for creating visual representations of data, such as graphs and charts. It is an essential part of the Python data science stack and is compatible with other popular libraries like NumPy and Pandas.

Additionally, Seaborn is a visualization library that is built on top of Matplotlib and provides users with easy-to-use tools for common data visualization tasks, such as mapping colors to specific variables or creating faceted plots.

Plotly is another data visualization library that can be implemented to analyze and present data through the creation of various types of charts and graphs, including statistical charts, scientific charts, 3D charts, multiple axes, and dashboards. With Plotly, users can easily create and customize interactive visualizations to gain insights and communicate their findings effectively. The preprocessing analysis has shoen that most employees reside in the United States of America.

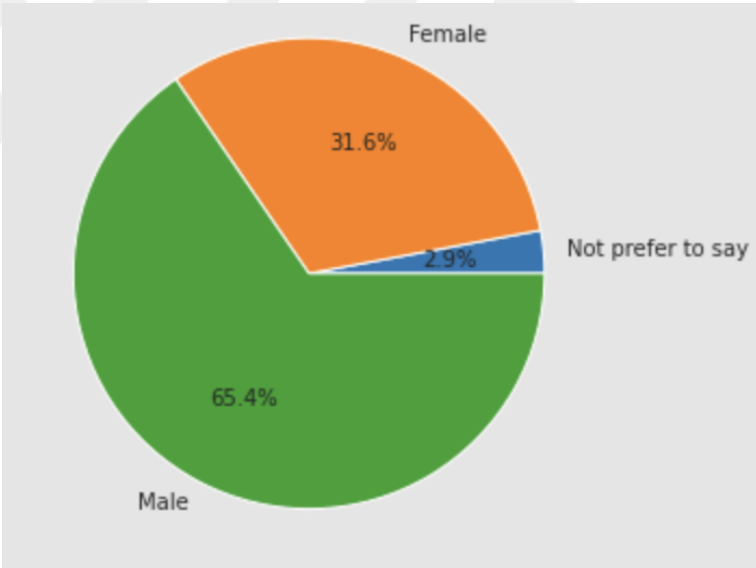

Figure 3.3 : Categorized OSMI Dataset by Gender.

Based on the analysis, from the figure (3.3), it can be observed that the majority of the statistical population in this study are men, accounting for approximately 65% of the participants. Women make up around 31% of the survey participants, while approximately 2.5% of people preferred not to disclose their gender.

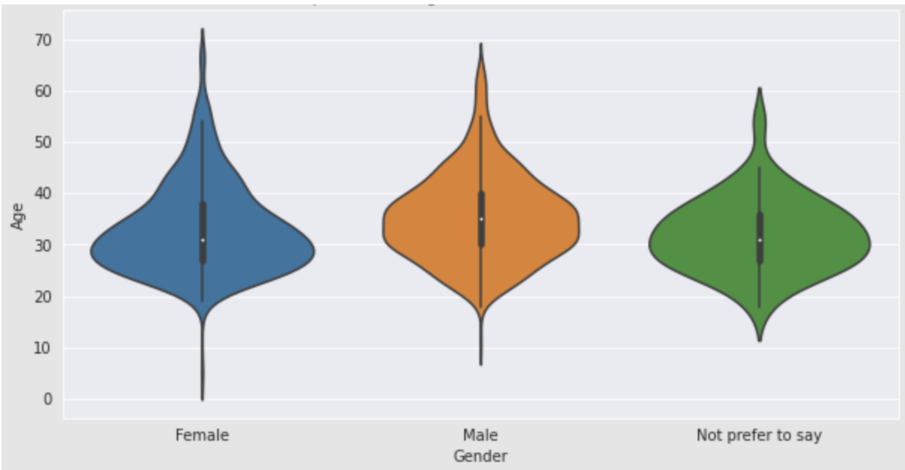

Figure 3.4 : Relationship between Age and Gender in the OSMI Dataset.

To investigate the relationship between gender and age in the OSMI dataset, a violin plot (3.4) is created using the Seaborn library. The plot shows that the density of male participants was wider over the age of 30, indicating that more men are aged 30 or older. In contrast, the density of female participants is wider around the age of 30, suggesting that women who participated in the survey tended to be around 30 years old or younger. This information can provide insights into the demographic composition of the OSMI dataset and may be useful for further analysis.

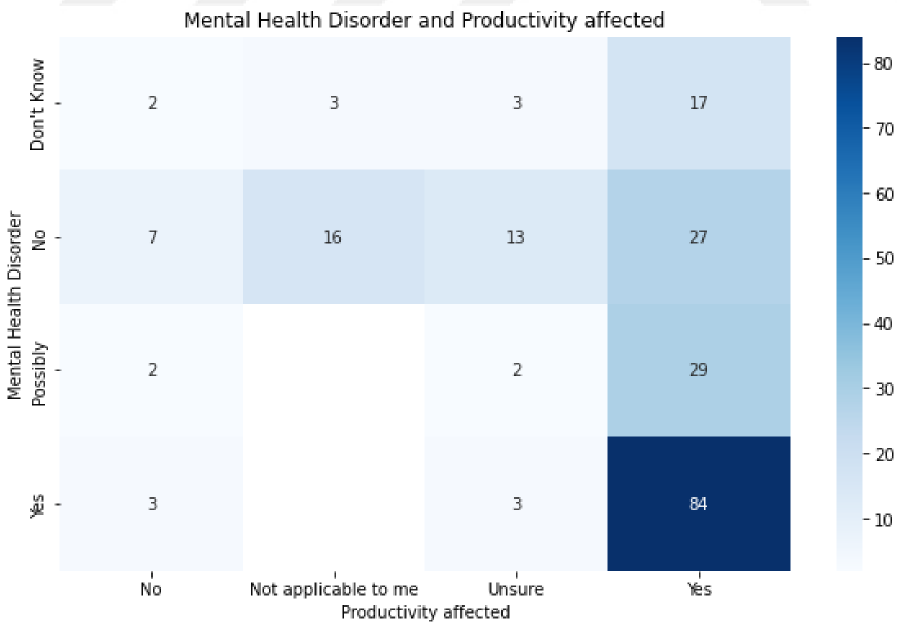

Figure 3.5 : Mental Health Disorder and Productivity Affected.

To conduct a preliminary analysis using preprocessed OSMI data, a heatmap in the figure (3.5) is utilized as a graphical representation of a data matrix. The heatmap displays each value as a color, with the intensity and magnitude of the color indicating the distribution of the data. The heatmap reveals that individuals who have experienced mental health disorders and perceive negative effects on their work productivity have a much higher density and magnitude of data compared to others.

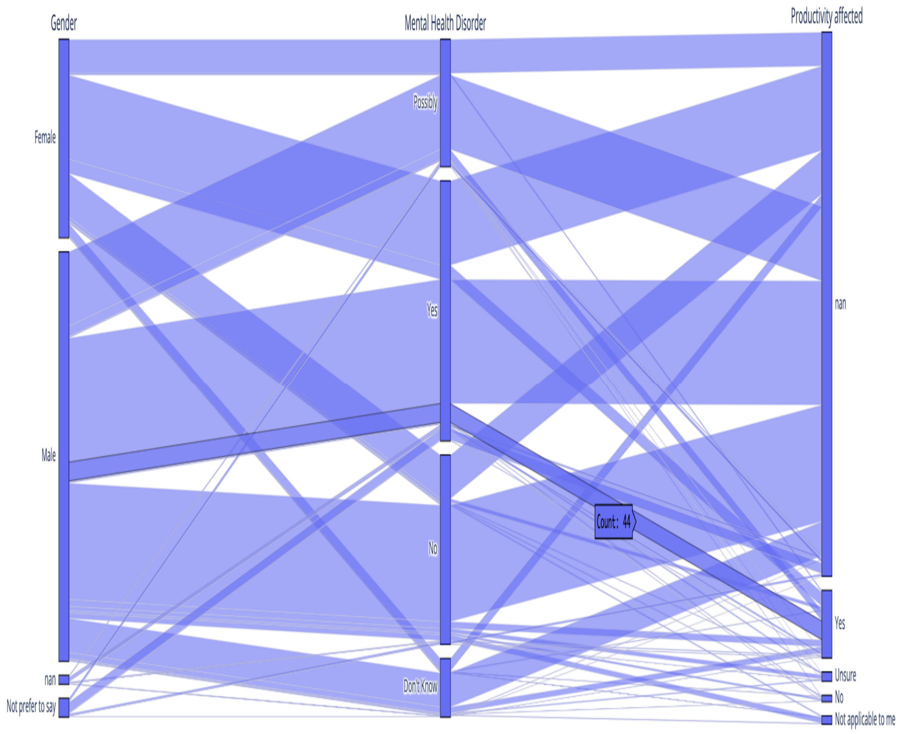

Figure 3.6 : Parallel Categories Diagram .

Another type of visualization diagram (3.6) that enables the exploration of relationships among several categorical variables in a single plot is known as a Basic Parallel Category Diagram. This diagram includes categorical variables such as “mental health disorders”, “productivity affected”, and “gender” displayed on the axis. The individual data points are connected with horizontal lines that represent each categorical variable. Additionally, the color of the lines can illustrate a third categorical variable, providing a visual representation of relationships among multiple variables. For instance, the diagram demonstrates that 44 men from the statistical population who experienced mental health disorders perceived a negative impact on their job productivity due to the disorder.

3.2 Generative Adversarial Network (GAN) Model

Goodfellow et al. [135] (2014) introduced the Generative Adversarial Network (GAN), which has become a significant development in the field of unsupervised deep generative models. GANs utilize an adversarial process to learn and capture the real data distribution. The generator G and discriminator D are the two components of GANs that are trained simultaneously using backpropagation to update the parameters of both the generator and discriminator networks. These networks are separate deep neural networks, where the generator's goal is to generate new samples and deceive the discriminator, while the discriminator's goal is to estimate the probability of distinguishing the real data distribution from a fake one. The generator takes a random noise vector z as input and outputs a generated sample $G(z)$, while the discriminator takes both a real sample Pdata and a generated sample $P(z)$ as input and predicts the probability of $D(x)$ or $D(G(x))$ [136].

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{\text{data}}(x)}[\log(D(x))] + \mathbb{E}_{z\sim p_z(z)}[\log(1-D(G(z)))] \tag{3.1}$$

Where,

D is discriminator, G is generator, $P_{\text{data(x)}}$ is the distribution of real data, $P(z)$ is the distribution of generator, x is the sample from $P_{\text{data(x)}}$, z is the sample from $P(z)$, $D(x)$ is the discriminator network, and $G(z)$ is the generator network.

GANs can be used to generate multi-dimensional data distributions, including images. GANs have shown promising results in difficult generative tasks [137] such as text-to-photo translation [138], image generation [139], image composition [140], and image-to-image translation [141]. However, GANs' training suffers from several issues, such as mode collapse and training instability [136].

GAN models lack control over the data they generate, especially when dealing with data that has multiple labeled classes [142]. As a result, additional information is necessary to direct the generated results towards specific labeled classes. To address this issue, a Conditional Generative Adversarial Network (CGAN) [118] was introduced as a means of controlling the data generation process in a supervised manner. CGAN combines random noise and conditional variable y to create a joint hidden representation of real data x. The generator function $G(z,y)$ is then used to direct the generated process, where y is an additional parameter.

As can be seen from eguation (3.2), the objective function for CGAN involves maximizing the discrimination accuracy of the discriminator function $D(x,y)$ while minimizing the error of the generator function $G(z,y)$.

$$\min\max V(D,G) = \mathbb{E}_{x\sim p_{\text{data}}(x)}[\log D(x|y)] + \mathbb{E}_{z\sim p_z(z)}[\log(1-D(G(z|y)))] \tag{3.2}$$

Conditional variable y can be text or a number that transforms the GAN model into a supervised model. CGAN can be used with images, sequence models, and other models, and it is useful for modeling complex and large-scale datasets that have different labels by adding conditional information y to both the generator and discriminator.

3.2.1 Pix2Pix and UNet architecture

The Pix2Pix model, which means takes a pixel of image then convert that into another pixel, introduced by Isola et al. [117], is successful variant of cGAN and a supervised image-to-image translation technique that has been widely accepted by the computer vision community for image synthesis across multiple domains. The key feature of the model is the combination of the conditional GAN (CGAN) loss [118] with the L1 regularizer loss, allowing the network to learn the mapping from input to output images and generate images that are as close to the ground truth as possible. The CGAN loss, represented in equation (3.3), involves random noise $z \sim p(z)$, while the L1 regularization loss, as shown in equation (3.4), also called the least absolute error, results in less blurring in the generated images by minimizing the sum of errors, computes the difference between the generated and ground truth images.

$$L_{CGAN}(G,D) = E_{x,y}[\log D(x,y)] + E_{x,z}[\log(1-D(x,G(x,z)))] \tag{3.3}$$

$$L_{L1}(G) = E_{x,y \sim Pdata_(x,y), z \sim P_(z)}[||y - G(x,z)||_1] \tag{3.4}$$

Pix2pix is a type of generator and discriminator framework that utilizes the Conditional Generative Adversarial Network (CGAN), and requires two images; an input image and the corresponding desired output image.

Isola et al. propose two options for training the Pix2pix model [117]. The first involves a generator architecture based on U-Net [143], which has an encoder/decoder (first a series of down sampling layers then we have bottle neck layer then a series of upsampling layers) with skip connections, allowing it to gather low-level information like the location of edges up to a bottleneck layer and ensure that the generated image has global coherence. The main objective of the generator is to learn a mapping function between the input image x and a random noise image z, which produces the output image y. In other words, it learns to map x, z to y, aiming to produce images that are indistinguishable from "real" images as perceived by the discriminator. The generator G is not only trying to reduce the loss from discriminator but also trying to move the fake distribution close to real distribution by using L1 or L2 loss. To be more precise, the loss function for the generator in the Pix2pix GAN consists of two components. The first component is the regular generator loss, which is typically associated with adversarial training. The second component is a weighted L1 loss that calculates the difference between the generated output (fake image) and the corresponding real image. By incorporating this weighted L1 loss, the generator aims to minimize the dissimilarity between the generated output and the ground truth data.

The second option is the PatchGAN [144] discriminator architecture, a fully convolutional network that classifies local image patches in the synthesized image as real or fake. That is, instead of classifying the entire image as either fake or real, the model uses a PatchGAN approach, which divides the image into N*N patches and predicts the authenticity of each pixel within those patches, allowing for more fine-grained discrimination between real and fake regions. A smaller value for N can be employed, even when it is significantly smaller than the full image size, and still yield high-quality outcomes. This is beneficial because a smaller PatchGAN requires fewer parameters, allowing for faster processing speed.

Additionally, this approach can be applied to images of any size, offering flexibility and scalability. As a whole, he discriminator D assesses both real and fake image pairs (x and y), and its objective is to differentiate between fake and real inputs. So, the fake image (generated by the generator) and the real image are provided as input to the discriminator. The discriminator then computes the loss by evaluating and comparing the authenticity of these two inputs.

The discriminator comprises a simple network architecture with downsampling layers. Towards the end, it utilizes a PatchGAN framework, which generates a grid of values or pixels. Each pixel in the grid is individually assessed and classified by the discriminator, indicating the extent to which it is considered real or fake on a scale of 0 to 1.

The training process of a Pix2pix GAN is similar to that of a regular GAN, with a slight modification in the generator's loss function. In addition to minimizing the loss determined by the discriminator, the generator G also incorporates an L1 or L2 loss component. This modification aims to not only reduce the discriminator's ability to distinguish real and fake samples but also align the generated distribution closer to the real distribution.

The equation (3.5) below represents the objective function of Pix2Pix:

$$\min_{G}\max_{D}\mathscr{L}_{\text{GAN}}(D,G)+\lambda\mathscr{L}_{\text{L1}}(G) \tag{3.5}$$

where, $\min_{G}$ denotes the minimization of the generator network, $\max_{D}$ denotes the maximization of the discriminator network, $\mathscr{L}_{\text{GAN}}(D,G)$ represents the adversarial loss, which quantifies the ability of the discriminator and generator to distinguish between real and generated data, λ is a hyperparameter that balances the importance of the adversarial loss and the L1 loss, and $\mathscr{L}_{\text{L1}}(G)$ represents the L1 loss, also known as the pixel-wise loss, which measures the similarity between the generated output and the ground truth.

3.2.2 Features and labels selection

In order to create a comprehensive image from the OSMI data, the question variables were scaled and divided into two categories: features and labels as shown in figure (3.7). Using a Python library, specific questions were selected as either input features or output labels based on the research questions and literature review. Two arrays, X and Y, were created from the larger data array by selecting specific columns of data using the indices contained in feature_idx and label_idx lists.

1		Featuer	Label	
2	0 Are you self-employed?	1		
3	1 How many employees does your company or organization have?	1		
4	2 Is your employer primarily a tech company/organization?	1		
5	3 Is your primary role within your company related to tech/IT?	1		
6	4 Do you know the options for mental health care available under your employer-provided health coverage?	1		
7	5 Has your employer ever formally discussed mental health (for example, as part of a wellness campaign or other official communication)?	1		
8	6 Does your employer offer resources to learn more about mental health disorders and options for seeking help?	1		
9	7 Is your anonymity protected if you choose to take advantage of mental health or substance abuse treatment resources provided by your employer?	1		
10	8 If a mental health issue prompted you to request a medical leave from work, how easy or difficult would it be to ask for that leave?	1		
11	9 Would you feel more comfortable talking to your coworkers about your physical health or your mental health?		1	
12	10 Would you feel comfortable discussing a mental health issue with your direct supervisor(s)?		1	
13	11 Have you ever discussed your mental health with your employer?		1	
14	12 Would you feel comfortable discussing a mental health issue with your coworkers?		1	
15	13 Have you ever discussed your mental health with coworkers?		1	
16	14 Have you ever had a coworker discuss their or another coworker's mental health with you?		1	
17	15 Overall, how much importance does your employer place on physical health?	1		
18	16 Overall, how much importance does your employer place on mental health?	1		
19	17 Do you have medical coverage (private insurance or state-provided) that includes treatment of mental health disorders?	1		
20	18 Do you know local or online resources to seek help for a mental health issue?	1		
21	19 If you have been diagnosed or treated for a mental health disorder, do you ever reveal this to clients or business contacts?		1	very important
22	20 If you have revealed a mental health disorder to a client or business contact, how has this affected you or the relationship?		1	
23	21 If you have been diagnosed or treated for a mental health disorder, do you ever reveal this to coworkers or employees?		1	very important
24	22 If you have revealed a mental health disorder to a coworker or employee, how has this impacted you or the relationship?		1	
25	23 Do you believe your productivity is ever affected by a mental health issue?		1	
26	24 If yes, what percentage of your work time (time performing primary or secondary job functions) is affected by a mental health issue?		1	
27	25 Do you have previous employers?	1		
28	26 Was your employer primarily a tech company/organization?	1		
29	27 Have your previous employers provided mental health benefits?	1		
30	28 Were you aware of the options for mental health care provided by your previous employers?	1		
31	29 Did your previous employers ever formally discuss mental health (as part of a wellness campaign or other official communication)?	1		
32	30 Did your previous employers provide resources to learn more about mental health disorders and how to seek help?	1		
33	31 Was your anonymity protected if you chose to take advantage of mental health or substance abuse treatment resources with previous employers?	1		
34	32 Would you have felt more comfortable talking to your previous employer about your physical health or your mental health?	1		
35	33 Would you have been willing to discuss your mental health with your direct supervisor(s)?		1	
36	34 Did you ever discuss your mental health with your previous employer?		1	
37	35 Would you have been willing to discuss your mental health with your coworkers at previous employers?		1	
38	36 Did you ever discuss your mental health with a previous coworker(s)?	1		
39	37 Did you ever have a previous coworker discuss their or another coworker's mental health with you?	1		
40	38 Overall, how much importance did your previous employer place on physical health?	1		
41	39 Overall, how much importance did your previous employer place on mental health?	1		
42	40 Do you currently have a mental health disorder?	1		

Figure 3.7 : Feature and Label Selection.

To obtain a comprehensive understanding of an employee's mental health condition for making decisions regarding treatment, recruitment, workplace environment, policy implementation, and various workplace programs, the entire dataset of 1458 respondents was scaled to the range of [-1,+1], and a portion of the data was selected to serve as input features, while others were designated as output labels in tables (3.2) and (3.3), respectively.

That is, the 59 potential features related to personal information could include various demographic, background, and employment-related factors about the employees. These features might encompass details such as age, gender, job position, department, tenure, performance ratings, etc. These features provide information about the employees that can be used for analysis and decision-making in the HR processes. On the other hand, the 24 labels related to mental illness are indicators or criteria that the HR department can utilize to identify potential mental health issues among employees. These labels might include self-reported symptoms, medical diagnoses, behavioral observations, or other assessments related to mental well-being. Out of these 24 labels, five specific labels are considered particularly important for HR, as they have been marked with an asterisk (*) in the selected label table. These asterisk-marked labels likely highlight critical indicators that require special attention from the HR department.

It is crucial to emphasize that the process of selecting questions as labels or features involves considering various factors that contribute to recognizing individuals with disorders and understanding mental health within the tech survey context. These characteristics can be categorized into different categories:

- Factors aiding recognition: The selection is based on factors that assist human resource professionals in identifying individuals with disorders. These factors include how individuals self-report their condition in different situations, such as past or present. For example, the questions may explore whether they disclose their illness, feel comfortable discussing it with previous employers, seek treatment, or experience interference from the disorder.
- Understanding mental health in the tech survey: The selected questions also help gauge how mental health is perceived among employees within the tech survey. This insight is valuable for understanding the prevailing attitudes, norms, and challenges related to mental health within the tech industry.
- Holistic evaluation: The chosen questions aim to identify individuals with mental health issues as a whole, without necessarily pinpointing specific types of disorders. The focus is on gaining a comprehensive understanding of the individual's situation, taking into account their self-reported experiences and challenges. (a holistic approach involves considering various factors such as self-reported experiences, symptoms, behaviors, emotions, and personal circumstances. Rather than focusing

on isolated symptoms or specific aspects, a holistic evaluation aims to capture the individual's overall well-being and functioning.)

- Self-reporting and identification: The self-reported nature of the questions is of particular importance. They provide insights into how individuals identify themselves, whether they consider themselves patients, or if they prefer to conceal their condition. This information is vital for human resource professionals during the hiring process and in understanding the needs and preferences of employees. It allows for tailored support and task allocation to optimize employee performance and well-being.

In summary, the selection of questions considers factors that aid in recognizing individuals with disorders, captures the perceptions of mental health within the tech survey, provides a holistic evaluation without specifying the disorder type, and focuses on self-reported experiences and identification for effective support and task management.

Furthermore, it is important to highlight that the selection of certain labels as the most important ones is driven by their utility in evaluating the performance of the generated images in the later stages of the proposed Pix2pix model. These labels play a crucial role in obtaining valuable results and assessing the effectiveness of the generated images.

Table 3.2 : Selected Features.

Feature	Question
F1	Are you self-employed?
F2	How many employees does your company or organization have?
F3	Is your employer primarily a tech company/organization?
F4	Is your primary role within your company related to tech/IT?
F5	Do you know the options for mental health care available under your employer-provided health coverage?
F6	Has your employer ever formally discussed mental health (for example, as part of a wellness campaign or other official communication)?
F7	Does your employer offer resources to learn more about mental health disorders and options for seeking help?
F8	Is your anonymity protected if you choose to take advantage of mental health or substance abuse treatment resources provided by your employer?
F9	If a mental health issue prompted you to request a medical leave from work, how easy or difficult would it be to ask for that leave?
F10	Overall, how much importance does your employer place on physical health?
F11	Overall, how much importance does your employer place on mental health?
F12	Do you have medical coverage (private insurance or state-provided) that includes treatment of mental health disorders?
F13	Do you know local or online resources to seek help for a mental health issue?
F14	Do you have previous employers? Tech Previous Employer Was your employer primarily a tech company/organization?
F15	Was your employer primarily a tech company/organization?
F16	Have your previous employers provided mental health benefits?
F17	Were you aware of the options for mental health care provided by your previous employers?
F18	Did your previous employers ever formally discuss mental health (as part of a wellness campaign or other official communication)?
F19	Did your previous employers provide resources to learn more about mental health disorders and how to seek help?
F20	Was your anonymity protected if you chose to take advantage of mental health or substance abuse treatment resources with previous employers?
F21	Would you have felt more comfortable talking to your previous employer about your physical health or your mental health?
F22	Did you ever discuss your mental health with a previous coworker(s)?
F23	Did you ever have a previous coworker discuss their or another coworker's mental health with you?
F24	Overall, how much importance did your previous employer place on physical health?
F25	Overall, how much importance did your previous employer place on mental health?

Table 3.2 (continued) : Selected Features.

Feature	Question
F26	Do you have a family history of mental illness?
F27	Have you observed or experienced an unsupportive or badly handled response to a mental health issue in your current or previous workplace?
F28	What is your age?
F29	What is your gender?
F30	What country do you live in?
F31	What is your race?
F32	What country do you work in?
F33	Have you had a mental health disorder in the past?
F34	Do you currently have a mental health disorder?
F35	Anxiety Disorder (Generalized, Social, Phobia, etc) (Past)
F36	Mood Disorder (Depression, Bipolar Disorder, etc) (Past)
F37	Psychotic Disorder (Schizophrenia, Schizoaffective, etc) (Past)
F38	Eating Disorder (Anorexia, Bulimia, etc) (Past)
F39	Attention Deficit Hyperactivity Disorder (Past)
F40	Personality Disorder (Borderline, Antisocial, Paranoid, etc) (Past)
F41	Obsessive-Compulsive Disorder (Past)
F42	Post-traumatic Stress Disorder (Past)
F43	Stress Response Syndromes (Past)
F44	Dissociative Disorder (Past)
F45	Substance Use Disorder (Past)
F46	Addictive Disorder(Past)
F47	Have you ever been diagnosed with a mental health disorder? (Past-to-Present)
F48	Anxiety Disorder (Generalized, Social, Phobia, etc) (Past-to-Present)
F49	Mood Disorder (Depression, Bipolar Disorder, etc) (Past-to-Present)
F50	Psychotic Disorder (Schizophrenia, Schizoaffective, etc) (Past-to-Present)
F51	Eating Disorder (Anorexia, Bulimia, etc) (Past-to-Present)
F52	Attention Deficit Hyperactivity Disorder (Past-to-Present)
F53	Personality Disorder (Borderline, Antisocial, Paranoid, etc) (Past-to-Present)
F54	Obsessive-Compulsive Disorder (Past-to-Present)
F55	Post-traumatic Stress (Past-to-Present)
F56	Stress Response Syndromes (Past-to-Present)
F57	Dissociative Disorder (Past-to-Present)
F58	Substance Use Disorder (Past-to-Present)
F59	Addictive Disorder (Past-to-Present)

Table 3.3 : Selected Labels.

Label	Question
L1:	Would you feel more comfortable talking to your coworkers about your physical health or your mental health?
L2:	Would you feel comfortable discussing a mental health issue with your direct supervisor(s)?
L3:	Have you ever discussed your mental health with your employer?
L4:	Would you feel comfortable discussing a mental health issue with your coworkers?
L5:	Have you ever discussed your mental health with coworkers?
L6:	Have you ever had a coworker discuss their or another coworker's mental health with you?
L7*:	If you have been diagnosed or treated for a mental health disorder, do you ever reveal this to clients or business contacts?
L8:	If you have revealed a mental health disorder to a client or business contact, how has this affected you or the relationship?
L9*:	If you have been diagnosed or treated for a mental health disorder, do you ever reveal this to coworkers or employees?
L10:	If you have revealed a mental health disorder to a coworker or employee, how has this impacted you or the relationship?
L11*:	Do you believe your productivity is ever affected by a mental health issue?
L12:	If yes, what percentage of your work time (time performing primary or secondary job functions) is affected by a mental health issue?
L13:	Would you have been willing to discuss your mental health with your direct supervisor(s)?
L14:	Did you ever discuss your mental health with your previous employer?
L15:	Would you have been willing to discuss your mental health with your coworkers or previouse mployees?
L16:	Have you ever sought treatment for a mental health disorder from a mental health professional?
L17*:	If you have a mental health disorder, how often do you feel that it interferes with your work when being treated effectively?
L18:	Have your observations of how another individual who discussed a mental health issue made you less likely to reveal a mental health issue yourself in your current workplace?
L19:	How willing would you be to share with friends and family that you have a mental illness?
L20*:	Would you bring up your mental health with a potential employer in an interview?
L21:	Are you openly identified at work as a person with a mental health issue?
L22:	Has being identified as a person with a mental health issue affected your career?
L23:	How has it affected your career?
L24:	Overall, how well do you think the tech industry supports employees with mental health issues?

3.2.3 Image extraction and preprocessing

In the first phase of the study, data was selected and organized into image. Each question was treated as a pixel, resulting in the generation of an 8x8 image for the features and a (5x5) image for the labels. This process yielded a total of 1458 images, with 1458 images containing (8x8) feature images and 1458 images with (5x5) label images. These single-channel (grayscale) image arrays that has been shown in figures (3.8), (3.9) respectively that can be utilized for various tasks related to mental health analysis.

Figure 3.8 : Feature Input (single-channel image)(8, 8, 1).

Figure 3.9 : Label Input (single-channel image)(5, 5, 1).

In the second phase of the study, the pixel intensities of both the source and target images were adjusted to fit within the range of [0, 1]. Pixel values in an image can be affected by various factors such as lighting conditions, camera settings, and image acquisition methods. By normalizing the pixel values to a standard range, the images can be better processed and analyzed. The command of exposure.rescale_intensity function takes an input image and an output range and scales the pixel intensities of the input image to the output range. In this case, the output range is set to (0, 1), which means that the pixel intensities of the input image are rescaled to lie in the range [0, 1]. To create color images, each grayscale image was converted from a single channel to a 3-channel RGB image. This was accomplished by replicating each grayscale image three times along the third dimension, which corresponds to the color channel. Finally, the newly created 3-channel RGB images were saved as two numpy arrays containing normalized and 3-channel source (1458, 8, 8, 3) and target (1458, 5, 5, 3) images.

In the third phase of the application, the dimensions of the source (8x8) and target (5x5) images (3.10) are adjusted to (256x256) (3.11) to ensure compatibility with various image-to-image translation tasks employed in subsequent sections.

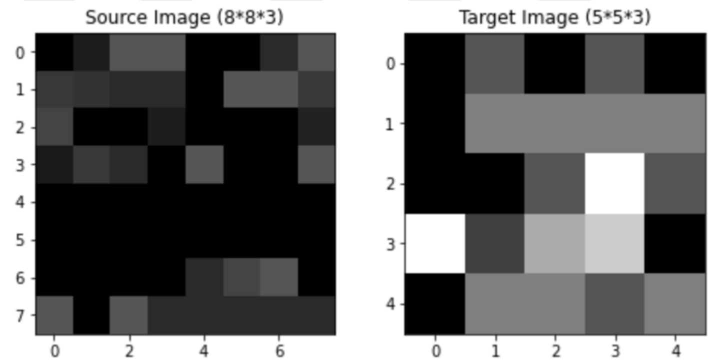

Figure 3.10 : Sample of Source Image and Target Image.

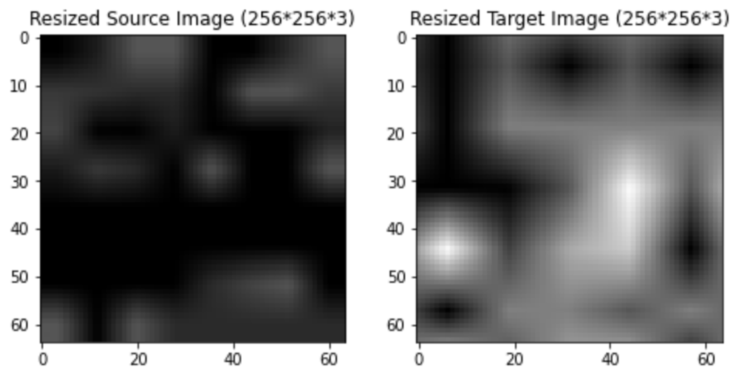

Figure 3.11 : Sample of Resized Source Image and Target Image (256*256*3).

To confirm whether the 'resize' function is being correctly applied to increase image size and adjust the picture size for a GAN model, in the Fourth phase, the original and resized images have been compared from a dataset randomly to assess how the 'resize' function affects the quality and resolution of the images. The comparison in the figure (3.12) is helpful for evaluating whether different image resizing methods are appropriate for a particular application such as Pix2pix GAN or not.

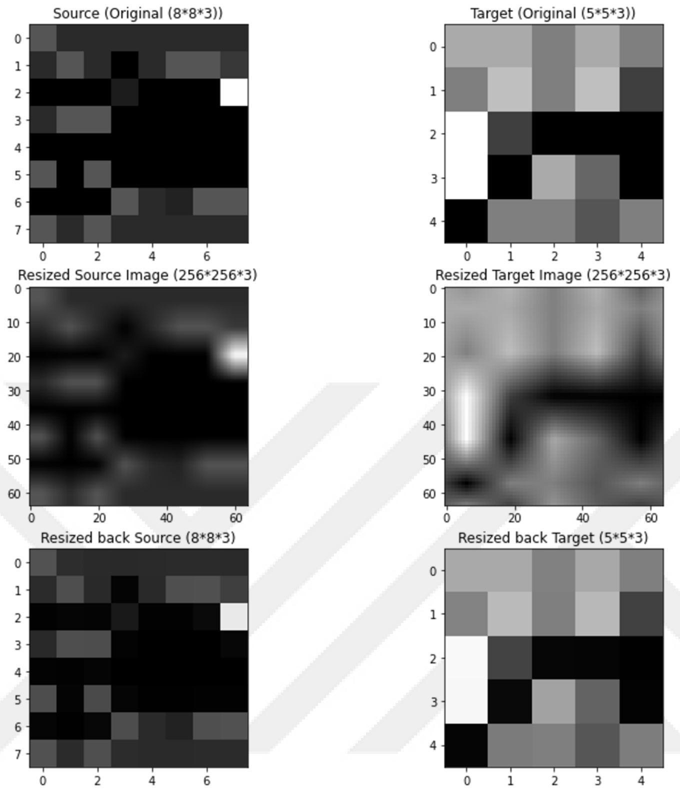

Figure 3.12 : Sample of Resized Backed Source Image and Target Image.

These images plot the original and resized images for the selected index in a (3x2) grid of subplots. The first row shows the original images in sizes (8x8) and (5x5). The second row shows the resized images at (256x256). The third row shows the images resized back down to (8x8) and (5x5). The subplot titles indicate the size of each image. After comparing the resized-back images with the source and target images, it can be inferred that the resize function did not alter the accuracy of either the source or target image. As a result, ensuring this step allows for the execution of the next phase.

During the fifth phase of the process, the two resized images 'resized source image' and 'resized target image' are concatenated to form a new image array named 'source_target_images'. The reason for concatenating these two images is two-fold. Firstly, Pix2pix GAN requires paired images as input. Secondly, by concatenating the source and target images, additional information is provided to the model, which can potentially enhance the quality of the generated images. The concatenation is done along the third axis (channel axis), which allows the generator to have more information about the desired output, leading to more realistic images.

Moreover, this concatenated image can help the discriminator distinguish between real and fake images more accurately by using information from both the source and target images. The 'np.concatenate()' method is used to concatenate these images, resulting in a new array 'source_target_images' with dimensions (1458, 256, 512, 3). This means that the array contains 1458 images, each with a resolution of (256 x 512) pixels, and each pixel is represented by three color channels (red, green, and blue).

The concatenated image serves as the source image, while the corresponding target image is used during the training process. By concatenating the images, the model can consider the relationship between the two images and generate a realistic output image that preserves these relationships. In summary, concatenating the images provides additional information to the model and enables it to generate better output images by considering the relationships between the source and target images. Figure (3.13) is presented as a sample of concatenated source and target images in the sample.

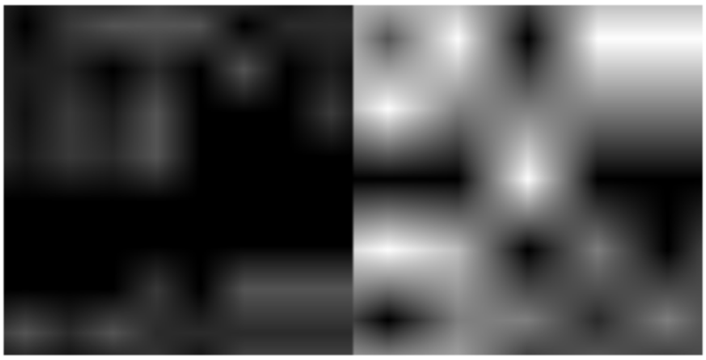

Figure 3.13 : Sample of Concatenated Source Image and Target Image.

In the Sixth phase, a dataset is split into training, validation, and test sets, which allows for measuring the GAN model's performance on various metrics such as accuracy, loss, and image quality. This helps to improve the GAN model's performance by adjusting its architecture, loss functions, and hyperparameters and ensures that the GAN model generalizes well to new, unseen data and is not simply memorizing the training set, and is essential for avoiding overfitting. This is typically done before applying any machine learning algorithm, including a GAN model. To split the 'source_target_images' dataset into training, validation, and testing sets, the train_test_split() function from the sklearn library is used, and the resulting sets are saved as distinct files. The 'source_target_images' array is sized (1458, 256, 512, 3), which means it has 1458 images, each with dimensions of (256x512) pixels and 3 color channels. 20% of the initial dataset will be allocated for testing, forming the "test_images" array that is (292, 256, 512, 3) in shape, consisting of 292 images for assessing the performance of the GAN model. The remaining 80% of the data is split into 64% for training and 16% for validation. The "train_images" array has a shape of (932, 256, 512, 3), containing 932 images that will be used to train the machine learning model, with the same size and color channels as the 'source_target_images' array. The "validation_images" array is (234, 256, 512, 3) in shape, consisting of 234 images that will be utilized for validation purposes during the GAN training procedure. As a result, the dataset is divided into training, testing, and validation sets and saved accordingly.

3.3 Proposed Model (Pix2Pix GAN)

The Pix2pix model is a type of Generative Adversarial Network (GAN) that is specialized in image-to-image translation. It uses an image-conditional GAN architecture, which enables it to generate large, high-quality images up to (256x256) pixels and perform well on a range of image-to-image tasks. Thanks to the carefully designed architecture, pix2pix has shown significant improvements over previous GAN models.

The Pix2pix GAN comprises two models, a generator and a discriminator. The generator creates synthetic images that closely resemble real images, while the discriminator distinguishes between real and fake images. During training, the discriminator is directly updated to become better at detecting synthetic images, while the generator is indirectly updated via the discriminator. This creates an adversarial relationship between the two models, where the generator tries to produce more realistic images to deceive the discriminator, while the discriminator tries to better identify fake images.

The Pix2pix model is categorized as a conditional GAN or cGAN, which means that it produces output images based on an input image, such as a source image. The discriminator model receives both the source and target images and evaluates whether the target image is a plausible transformation of the source image. During training, the generator model uses adversarial loss to create realistic images in the target domain. Additionally, the generator is updated through L1 loss, which measures the difference between the generated image and the intended output image. This L1 loss helps the generator to produce more accurate translations of the source image.

Based on the goal of the research, the proposed model uses the pix2pix GAN [145] algorithm for image-to-image translation. The generator model is designed based on the U-Net architecture, which consists of an encoder and a decoder. The encoder compresses the input image into a low-dimensional feature vector, and the decoder reconstructs the output image from the feature vector. In other words, the U-Net architecture is employed in the generator model to produce output images from input images. The encoder architecture consists of eight convolutional layers with decreasing spatial dimensions and increasing number of filters (C64-C128-C256-C512-C512-C512-C512-C512) and uses LeakyReLU activation function with a slope of 0.2. The first encoder layer is batch normalized. There are two batch normalization layers in the generator. One is in the encoder, specifically in the first layer of the encoder. The other is in the decoder, which is applied to all the layers except the bottleneck layer.

The generator of the pix2pix GAN has a neural network architecture that includes a dropout layer with a 0.5 rate. The purpose of this layer is to decrease overfitting during training by randomly dropping out some of the neuron outputs. This technique compels the model to acquire more varied and adaptable representations, ensuring it does not rely too much on a single neuron. Therefore, adding dropout to the generator in the pix2pix GAN can be advantageous in preventing overfitting and improving the model's performance. Nevertheless, several other factors, such as the model architecture, data quality and quantity, and the training process, can also contribute to overfitting in the model [146].

The decoder, on the other hand, has transposed convolutional layers with decreasing numbers of filters (C512-C512-C512-C512-C256-C128-C64) and ReLU activation function. All decoder layers except the last one are subject to dropout. The bottleneck layer is a convolutional layer with 512 filters, kernel size of 4x4, stride of (2x2), and ReLU activation function. The ReLU activation function is used for introducing non-linearity to the model, which is necessary for fitting complex data. In the provided generator architecture, a stride value of (2x2) is utilized in both the convolutional and transposed convolutional layers. This allows for downsampling of the input image in the encoder, and upsampling of the feature maps in the decoder, leading to an increase in spatial dimensionality of the output image. As a result, the activation function used in the encoder is a leaky rectified linear unit (LeakyReLU), while the activation function used in the bottleneck layer and decoder is a rectified linear unit (ReLU).

The encoder and decoder in the proposed model are linked through skip connections, and the bottleneck layer has 512 filters. The output image size is the same as the input image size and uses a tanh activation function. To ensure effective learning, the model's weights are initialized from a Gaussian distribution with a mean of 0 and a standard deviation of 0.02. The generator of the model has 54,419,459 trainable parameters, which means that it is capable of learning a large number of complex transformations to generate high-quality outputs. While, the model has 9,856 non-trainable parameters, which means that these values are fixed and cannot be updated during training. These parameters may include things like the architecture of the model, the number of layers or nodes in each layer, or other hyperparameters that were set before training began.

The discriminator function takes an input image with a default size of (256x256x3). The discriminator architecture consists of convolutional layers with batch normalization and LeakyReLU activation functions, arranged in a (C64-C128-C256-C512) structure with a receptive field size of (70x70). The discriminator's weights are initialized from a Gaussian distribution with a mean of 0 and a standard deviation of 0.02.

The discriminator network has two inputs, the source input image and the target input image, which are concatenated channel-wise. The first layer of the network is C64, followed by subsequent layers of C128, C256, and C512. Each of these layers has batch normalization and LeakyReLU activation functions. Four batch normalization layers are used in the discriminator function to improve the performance and stability of the network. It helps to normalize the activations between layers, which can reduce the internal covariate shift problem that can occur during training. They are added after the second, third, fourth, and fifth convolutional layers. The first convolutional layer doesn't use batch normalization. The last layer of the network is a convolution layer that uses a sigmoid activation function to output a 1-dimensional patch. In the discriminator of the proposed model there are a total of 6,968,257 parameters, out of which 6,965,441 are trainable and 2,816 are non-trainable. This means that during the training process, the model will adjust the weights and biases of 6,965,441 parameters to optimize its performance, while the remaining 2,816 parameters will remain fixed. These non-trainable parameters are typically used for tasks such as normalization or regularization, where fixed parameters are used to constrain the model's behavior.

To train the model, a binary cross-entropy loss function is used and optimized with the Adam optimizer. The Adam optimizer has a learning rate of 0.0002 and a $\beta 1$ value of 0.5, and the value of 0.5 is commonly used for β because it is seen as a reasonable compromise between encouraging gradient norms close to 1 (which helps with stability) and allowing enough gradient variation to avoid overfitting. It is worth to mention that the Adam optimizer is created with a learning rate of 0.0002 and a $\beta 1$ value of 0.5, and it is used to compile the discriminator model along with the binary cross-entropy loss function and the accuracy metric in discriminator and this combination is commonly used in GANs and has been found to work well in practice. The binary cross-entropy loss function is used to measure the difference between the predicted and actual labels in the discriminator, and the accuracy metric is used to evaluate the performance of the discriminator during training.

The final step in building the image-to-image translation model involves creating a composite model that connects the generator model's output to the discriminator model's input. This composite model consists of the generator and discriminator models, as well as the input image shape. The generator generates an output image from the input image, which is then fed into the discriminator along with the original input image. To prevent the discriminator from changing during the generator's training, its trainable attribute is set to false. The composite model calculates the loss function using the outputs of the generator and discriminator models, which is a combination of the adversarial loss (measuring how well the generator fools the discriminator) and a L1 loss (measuring the difference between the generated image and the real image). The loss function is weighted by the contribution of each model output, and the model is compiled using the Adam optimizer, which can efficiently and effectively update the weights of the model during training to minimize the specified loss function. The GAN composite model has a total of 61,397,572 parameters, with 54,419,459 being trainable parameters and 6,978,113 being non-trainable parameters, the trainable parameters are the model parameters that are updated during the training process in order to minimize the specified loss function. So, they likely include the weights and biases of the generator and discriminator models. The non-trainable parameters are typically fixed parameters that are set during the construction of the model and do not change during training, and they may include aspects of the model architecture such as the input shape and layer dimensions.

In total, the resulting model is a GAN that can be used for image-to-image translation. The GAN model has two input layers (one for the input image and one for the generator's output) and two output layers (one for the discriminator's output and one for the generator's output). Additionally, several utility functions are used to train the GAN model for image-to-image translation.

The GAN model iteratively trains over epochs of 200, which the choice of the number of epochs depends on the size and complexity of the dataset, the capacity of the models, and the desired level of performance.

Batch size is equal to 1, meaning that each batch will contain only one image, which is a typical choice for GAN models that operate on high-resolution images. This may lead to potentially noisy gradients and slower convergence compared to larger batch sizes. However, it allows for more control and fine-tuning as the model focuses solely on the specific image and its corresponding target during each update. Additionally, training with a batch size of 1 can be beneficial when dealing with limited computational resources or when working with images that require significant memory to process. This is because the memory requirements for training GANs on high-resolution images can be very high, and reducing the batch size helps to alleviate this issue.

The number of patches that are extracted from each image during training is considered 16 . In this implementation, the generator and discriminator operate on (256x256) images, and each image is divided into 16 patches of size (32x32). The discriminator predicts the authenticity of each patch separately, and the generator is trained to generate each patch independently. This approach can help to reduce the artifacts that can be introduced by the generator when generating high-resolution images.

Furthermore, no random jitter will be applied to the images during training. Random jittering refers to a technique where small random transformations are applied to the input images during each training iteration, such as random cropping, flipping, and rotation. This technique can help to increase the robustness of the model and improve its generalization performance. However, it can also increase the computational cost of training.

The training will start at the beginning, and the model state is saved every 10 epochs during training. It's important to mention that two functions, start_training and resume_training, are used to train a GAN on an image dataset. The start_training function is used to start training from the beginning, while the resume_training function is used to continue training from a saved step. In this case, the model was trained on the entire dataset of 932 images for 150 epochs before being saved at a particular step. Therefore, the step number used to resume training is 139800, which corresponds to the point at which training had previously stopped.

3.4 Architecture of Proposed Model (Pix2Pix GAN)

Pix2Pix proposed method involves generating new images based on source and target images and can be used for various applications, including image enhancement, super-resolution, feature transfer, segmentation, and more. Pix2pix GAN is a type of U-Net generator that differs from regular GANs in that it does not take noise as input.

Instead, the input consists of a source and target image, with noise being indirectly introduced during training and testing through dropout layers [117,147].

The architecture of the generator, discriminator, and pix2pix GAN model used in this research is illustrated in the figures (3.14), (3.15), (3.16), (3.18), and (3.14), and exhibited in the following pages. The generator model takes in input 6, which is a noise vector utilized to create synthetic images. On the other hand, the discriminator model accepts two inputs: input 7 for real images and input 8 for fake images. In the GAN model, input 9 is the noise vector used to generate fake images, which is initially inputted to the generator. The generator's output is then fed to the discriminator alongside the actual images for evaluation.

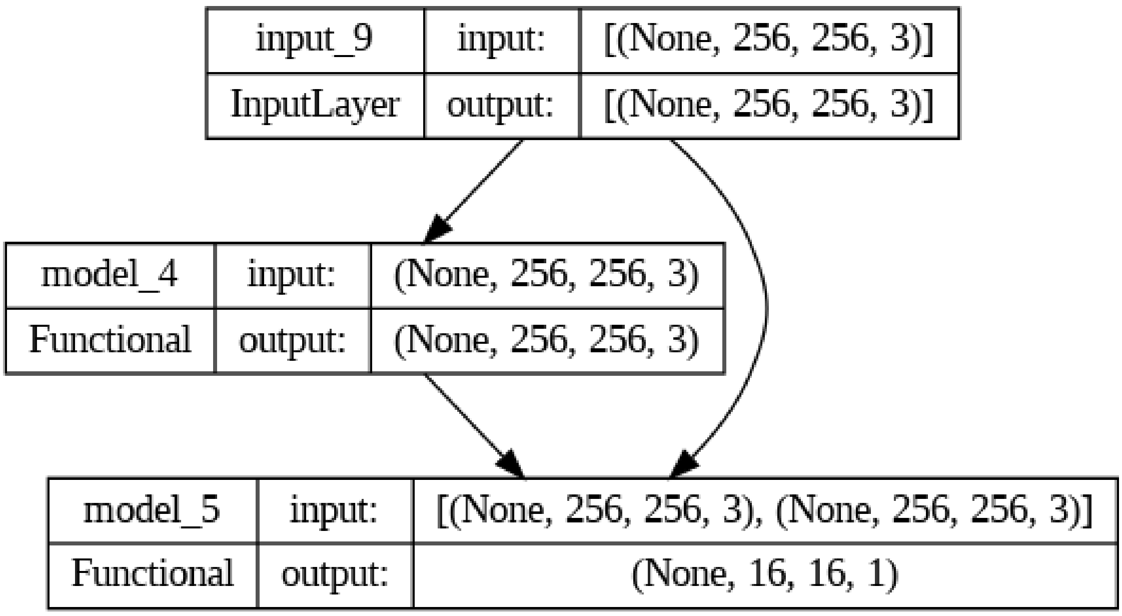

Figure 3.14 : GAN Architecture.

3.4.1 Generator network

The generator's loss function is a combination of adversarial and L1 loss, and based on the architecture (3.15) the generator network takes an input of shape (none, 256, 256, 3) which represents a noise vector used to generate fake images. So, the first layer in the network is an InputLayer with output shape (none,256,256,3), which essentially just passes the input through to the next layer. The second layer is conv2d_22 with input shape (none, 256, 256, 3) and output shape (none, 128, 128, 64). This layer applies a convolution operation to the input to extract features, resulting in a feature map with 64 channels. The output of this layer is then passed through a LeakyReLU activation function with an output shape (none,128,128,64), which introduces non-linearity into the network.

The third layer, Conv2d_23, has an input shape (none, 128, 128, 64) and an output shape (none, 64, 64, 128). This layer applies another convolution operation to the previous layer's output to extract higher-level features. Again, the output is passed through a LeakyReLU activation function. The fourth layer is batch_normalization_30 with input shape (None, 64, 64, 128) and output shape (None, 64, 64, 128). This layer normalizes the outputs of the previous layer to help stabilize and speed up training.

The architecture continues with several more layers of Conv2D, LeakyReLU, BatchNormalization, and upsampling (using Conv2DTranspose) layers until the penultimate layer, which is an activation layer named activation_21 with input (none, 128, 128, 128) and output (none, 128, 128, 128). The last layer of the generator is conv2d_transpose_23 with input (none, 128, 128, 128) and output (none, 256, 256, 3), which is a Conv2DTranspose layer that produces the final output image with the same dimensions as the input image.

The figure (3.15) represents various layers in different colors. The InputLayer is depicted in yellow, Conv2D in pink, LeakyRelu in green, BatchNormalization in blue, Conv2DTranspose in dark green, Dropout in yellow, Concatenate in pink, and Activation in green.

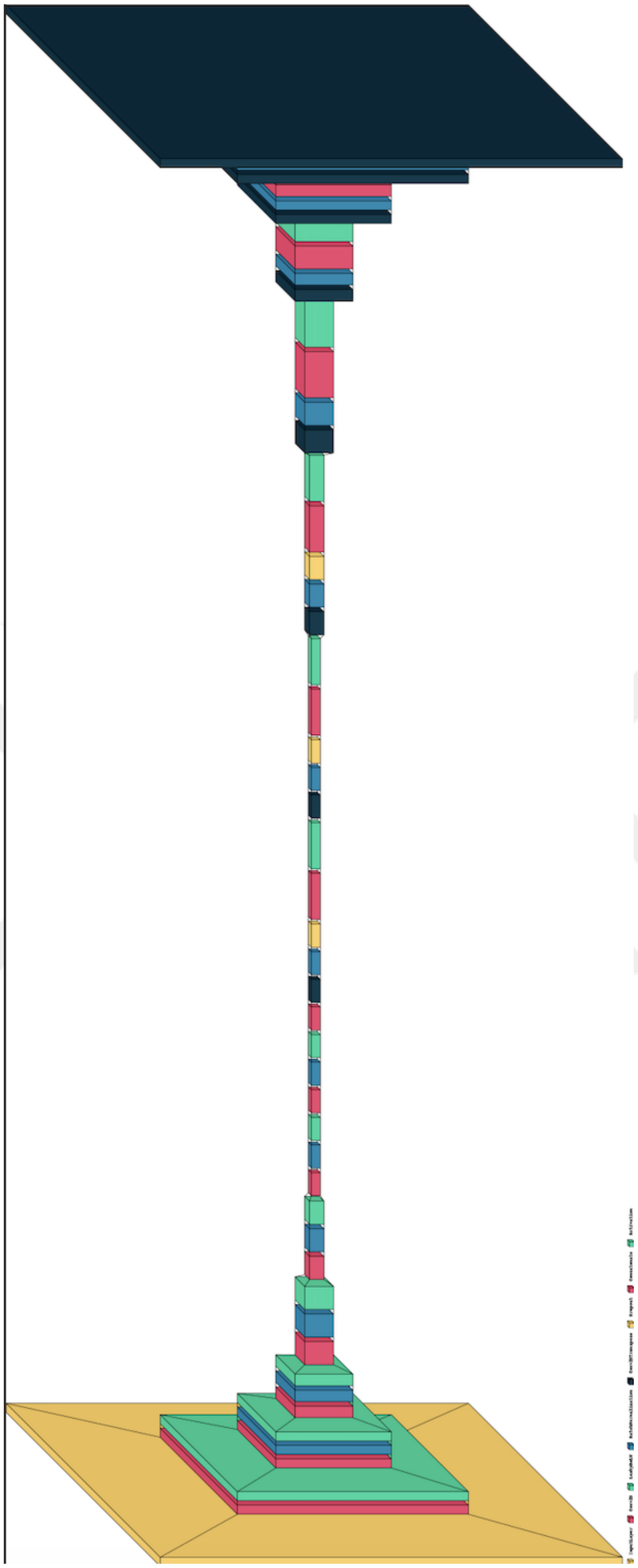

Figure 3.15 : Visual Representation of Generator’s Layers.

3.4.2 Discriminator network

In Pix2pix GAN, the discriminator is trained in a similar way to the simple GAN by maximizing the difference between real and generated images. And also,The discriminator used in pix2pix GAN is PatchGAN, which is a deep CNN (Convuloution Neural Network) that classifies patches of the input image as real or generated rather than processing the entire image at once. Typically, the patch size is set to (70x70) pixels, and the final prediction is obtained by averaging the predictions made for each patch.

The discriminator architecture of proposed GAN takes two inputs, with shapes (none, 256, 256, 3) and (none, 256, 256, 3), respectively, as shown in the figure (3.18). The two inputs are fed through separate InputLayer with outputs (none, 256, 256, 3). Then, the two outputs are concatenated using Concatenate layer with output shape (none, 256, 256, 6).

The concatenated output is then fed into a series of convolutional layers. The first convolutional layer is Conv2D layer with a filter size of 64, a stride of 2, a kernel size of 4x4, and with output shape (none, 128, 128, 64) followed by LeakyReLU activation layer with a negative slope of 0.2 and output shape (none, 128, 128, 64). The output is then passed through another Conv2D layer with output shape (none, 64, 64, 128) and a BatchNormalization layer with output shape (none, 64, 64, 128). This is followed by another LeakyReLU activation layer with output shape (none, 64, 64, 128). This pattern continues with additional Conv2D layers, each followed by a BatchNormalization layer and a LeakyReLU activation layer.

The last two convolutional layers are Conv2D layers with output shapes (none, 16, 16, 512) and (none, 16, 16, 1), respectively. The final activation layer is a sigmoid function which takes the output of the last Conv2D layer as input and produces the output of shape (none, 16, 16, 1).

The figure (3.16) depicts various layers, each represented by a different color. The InputLayer is visualized in yellow, Concatenate in pink, Conv2D in green, LeakyRelu in blue, BatchNormalization in dark green, and Activation in yellow.

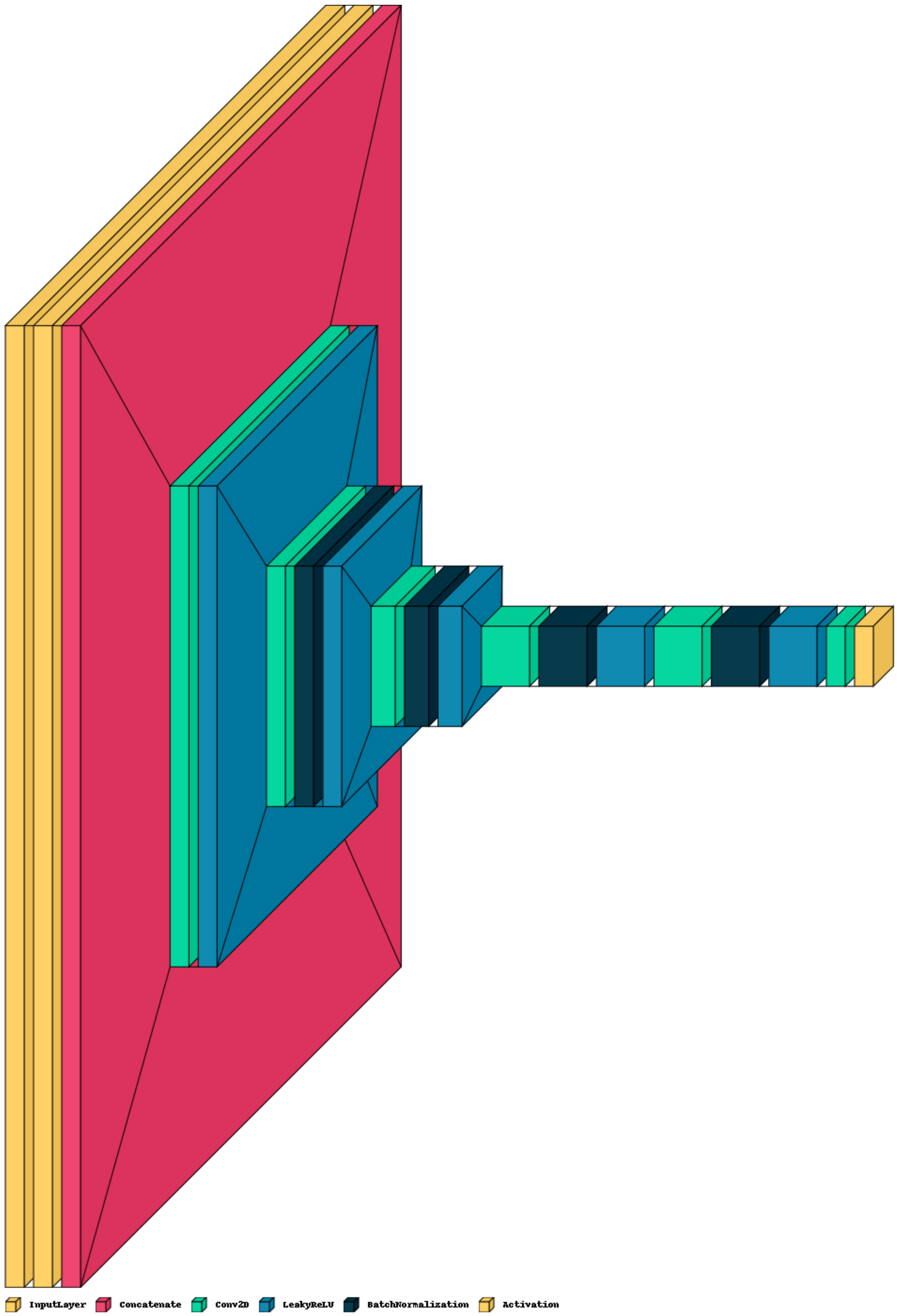

Figure 3.16 : Visual Representation of Discriminator's Layers.

3.4.3 Pix2Pix GAN network

In the Pix2pix GAN architecture, the generator takes an input image and generates a corresponding output image, while the discriminator tries to distinguish between the generated image and the real image.

The architecture with input 9 (none, 256, 256, 3) begins with an InputLayer that takes an image of size (256x256) with 3 color channels (RGB) and outputs the same size image. The next layer is called model_4, which takes the input image and applies a series of convolutional layers, each followed by a batch normalization layer and a ReLU activation function. This series of layers is designed to extract feature maps from the input image and encode them into a lower-dimensional space. The final output of this layer is also an image of the same size as the input image.

The last layer is called model_5, which takes the output of model_4 and uses a series of convolutional layers, each followed by a batch normalization layer and a LeakyReLU activation function. The final layer of this sequence is a convolutional layer with a single output channel, which produces a 16x16 image.

It's worth to mention that the output image of the generator is not directly produced by the last layer of model_5. Instead, the generator produces a (256x256) image with 3 color channels, and the loss function used during training compares this output to the real target image. The discriminator takes both the generated and real images as inputs and tries to distinguish between them, forcing the generator to produce more realistic outputs.

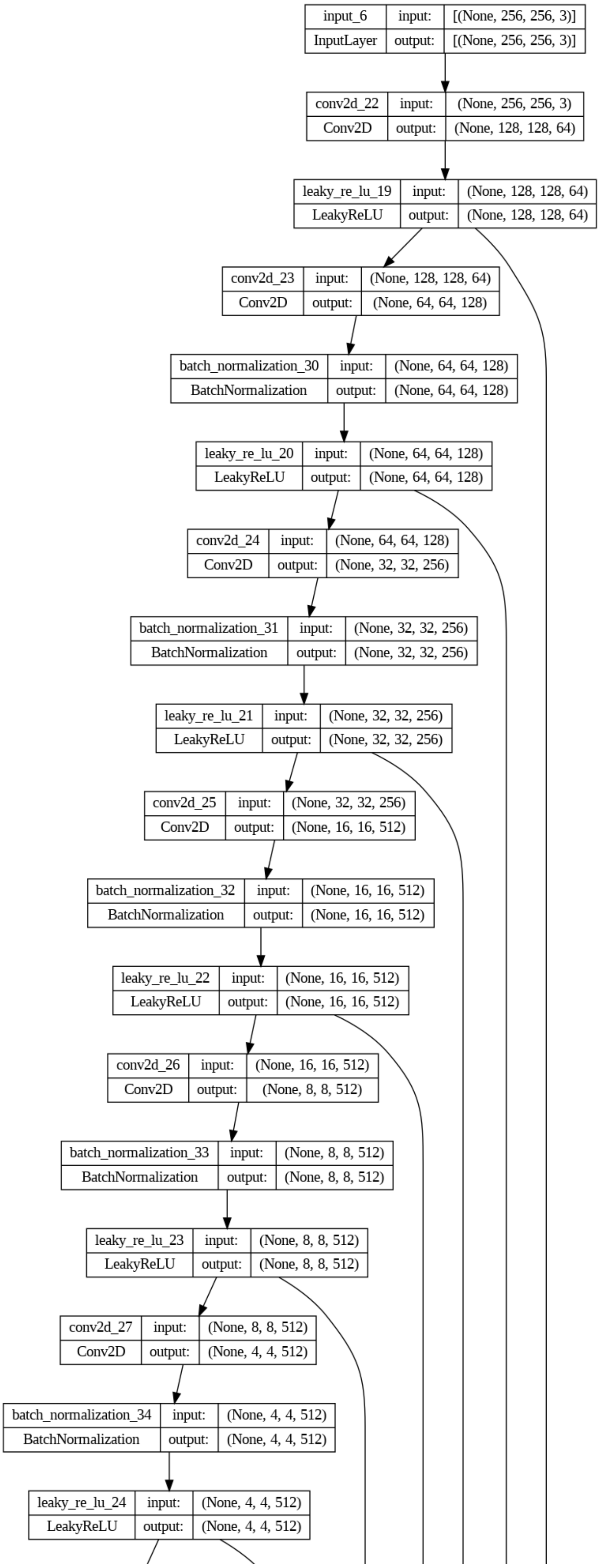

Figure 3.17 : Generator Architecture.

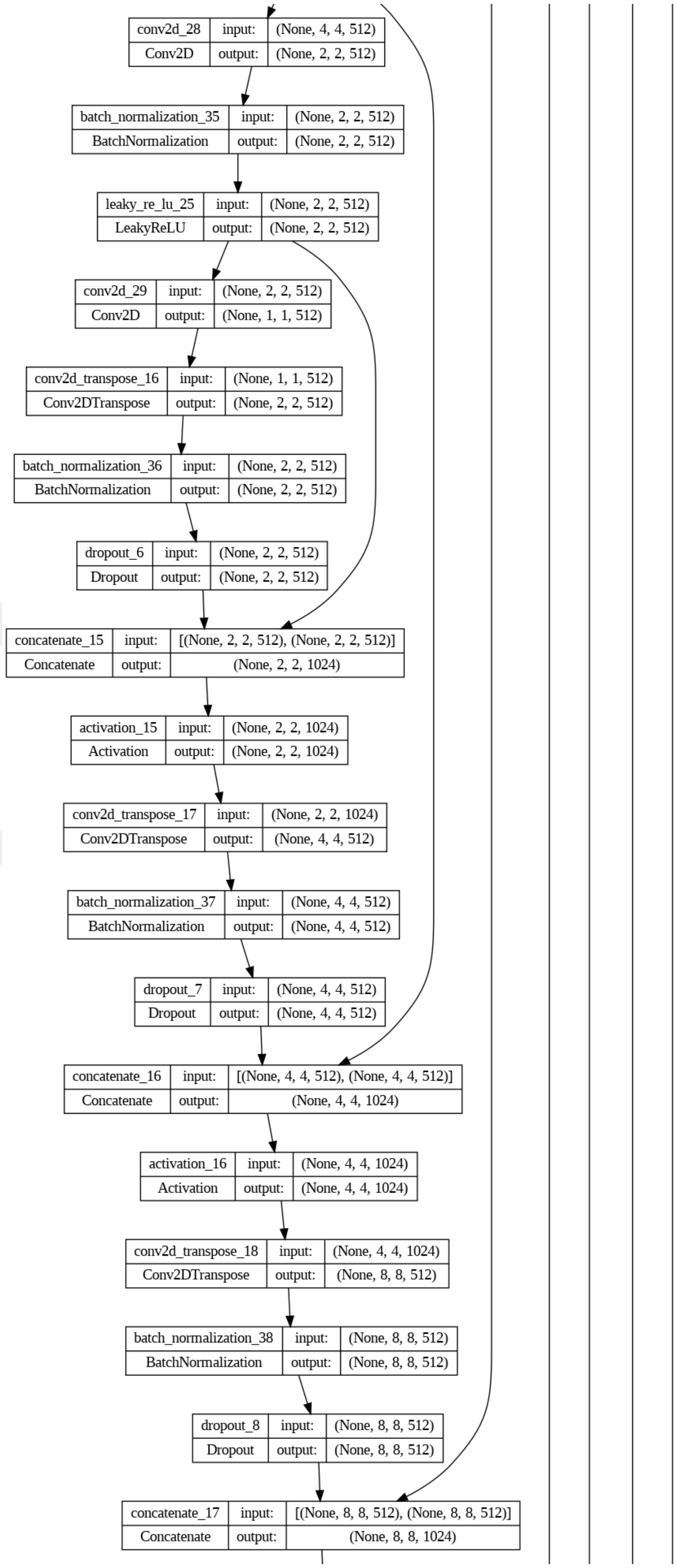

Figure 3.17 (continued) : Generator Architecture.

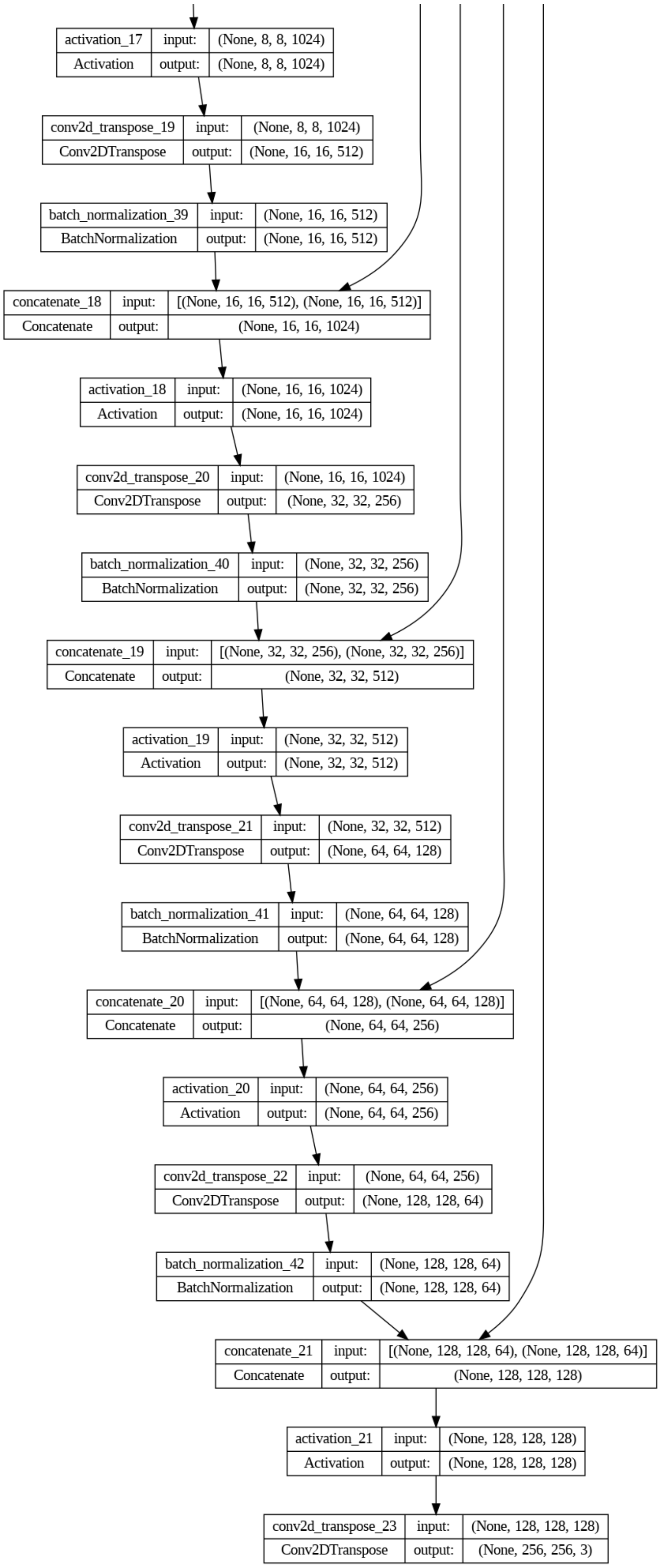

Figure 3.17 (continued) : Generator Architecture.

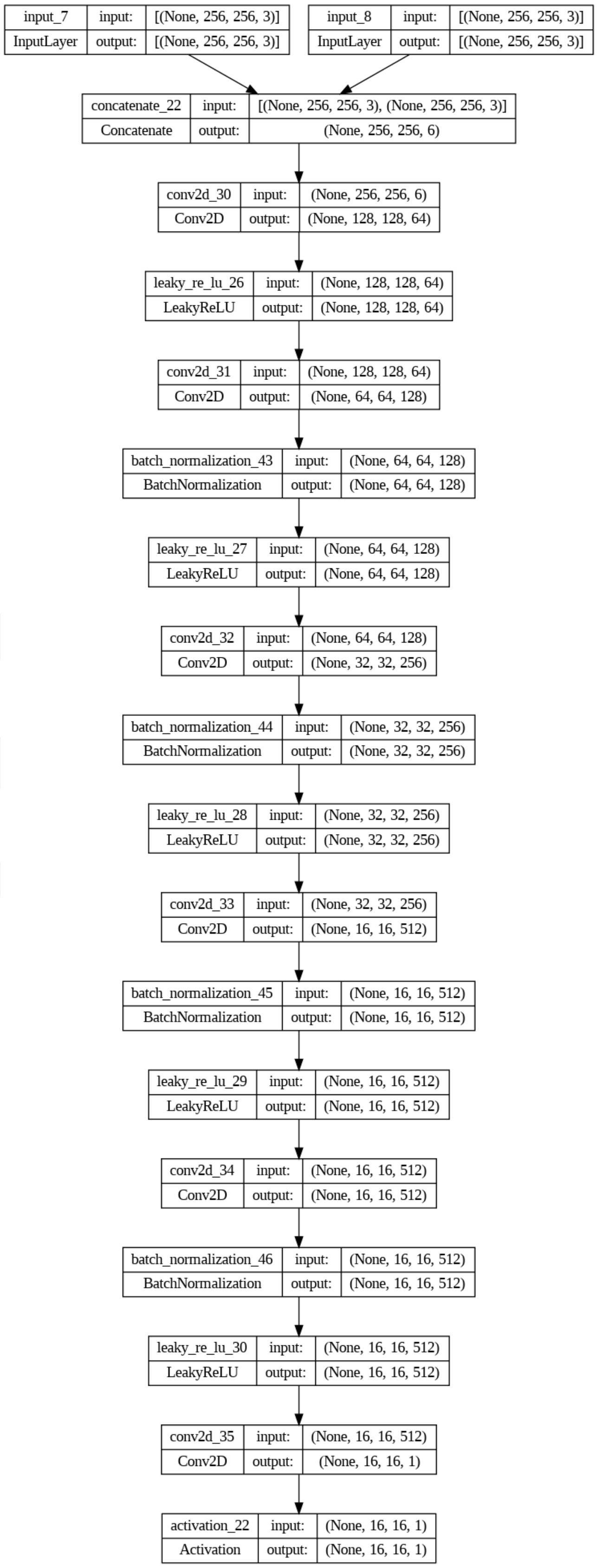

Figure 3.18 : Discriminator Architecture.

4. RESULT ANALYSIS and DISCUSSION

4.1 Mental Health Image (MHI)

Mental Health Images (MHI) extracted from OSMI data offers several advantages that can be highly beneficial for employees' situations. These images provide a deeper understanding of mental health experiences, which cannot be solely captured through self-reported data, as images can capture nonverbal expressions of emotions and reveal details about people's daily lives.

Additionally, this data can help in identifying patterns and trends related to mental health issues among employees. This information can be utilized to predict the health of prospective employees or plan for the treatment of current workers. Finally, it can assist human resource employers, mental health practitioners, and policymakers in better understanding the impact of workplace environmental factors on mental health, leading to the development of targeted interventions for addressing these issues.

4.2 Implementation

The feature and label images are created by preprocessing OSMI data, based on previous studies and some additional criteria. These images represent demographic data, symptom profiles, and other relevant information that is used to diagnose and classify a variety of mental health conditions. The suggested model is an image-to-image translation model that has been implemented using the Keras and TensorFlow environment. The proposed pix2pix GAN model for Mental Health Disorders (MHD) is designed to generate high-quality images of mental health disorders from OSMI data. It utilizes a U-Net architecture, which is a popular architecture for image segmentation tasks that allows for precise localization of objects in an image, particularly when dealing with limited amounts of labeled data. The GAN model takes two input models, a generator model (g_model) and a discriminator model (d_model), as well as an input shape for the images that will be generated.The model is trained using a dataset consisting of pairs of feature images and corresponding label images. The generator takes the feature images as input and generates new predicted label images. The discriminator evaluates the generated image and determines whether it is a real image or a fake image generated by the generator. During the training procedure, the generator and the discriminator are trained in an adversarial manner. The generator tries to generate images that are realistic and similar to the actual images of mental health disorders, while the discriminator tries to distinguish between the real and fake images. Over time, the generator becomes better at generating high-quality images that are indistinguishable from the actual images of feature images. Once the model is trained, the extracted mapping function will be used to predict the unseen feature images to predict the label image as generated output.These generated images can be used for a variety of applications, including research, diagnosis, and treatment of mental health disorders.

4.3 Evaluation

The Pix2pix GAN is able to generate an output image that closely resembles a target image by using a source image as input. Because of this, the quality of the generated image is the most important factor in evaluating the model's performance. To evaluate the model, a single model is chosen from a range of models at different epochs, and an input image is given. The input image is divided into a source image and a target image, and the model generates a new image from the source image. The prediction function then returns the generated image and the original target image. The quality of the generated image is assessed by comparing it with the target image using various scientific metrics. Therefore, the generated image is the main focus of evaluation because it represents the quality of the model's performance as it is the output produced by the model.

The Pix2pix method trains a model on data to classify and predict results. This model was trained with the ADAM optimizer by setting $\beta 1 = 0.5$, $\beta 2 = 0.999$, and the initial learning rate was set to 0.0002. The total learning time was around 4 hours. The data is split into three subsets during the learning process: training, validation, and testing. By comparing metrics between these subsets, the model can be evaluated for its performance. By comparing the values of certain metrics between the training and testing sets at different epochs, it would be possible to determine how well a model can generalize to new and unseen data, and thus assess its performance.

Previous studies [148,149] commonly use PSNR, SSIM, SAM, SRE, and UIQ as metrics to evaluate image processing models. However, these metrics may not always provide good indications of overfitting. Instead, a common approach is to compare the MAE and RMSE values of the training set and validation set as a metric for detecting overfitting. Additionally, visualization techniques can also be employed for better understanding. Overfitting [150] occurs when a model becomes overly complex and starts to memorize the training data, leading to poor performance on new, unseen data. One way to detect overfitting is to monitor the difference in performance between the training set and validation set during training. If the model performs significantly better on the training set than on the validation set, it may be overfitting.

In this study, the performance of the proposed model is evaluated through various metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), Signal-to-Reconstruction Error Ratio (SRE), Spectral Angle Mapper (SAM), and Universal Image Quality Index (UIQ). These metrics are defined as follows:

4.3.1 Mean absolute error

MAE (Mean Absolute Error) formula (4.1) pixel-to-pixel comparison is shown as below:

Formula:

$$MAE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} |S(i,j) - G(i,j)| \tag{4.1}$$

MAE measures the average absolute difference between the pixel values of the original (source) image $S(i,j)$ and the reconstructed (generated) image $G(i,j)$ at corresponding locations. It is a common evaluation metric used in image processing to assess the overall difference between two images. MAE values range from 0 to ∞ , with lower values indicating better image similarity.

The tables (4.1) and (4.2) display the MAE values for various epochs of the proposed model applied to OSMI Mental Health Image:

Table 4.1 : MAE Values for Different Models till Epoch 100.

Model	Epoch	Value	Epoch	Value	Epoch	Value	Epoch	Value
Train	10	0.064	30	0.036	70	0.029	100	0.022
Test	10	0.064	30	0.054	70	0.062	100	0.063
Val	10	0.064	30	0.054	70	0.062	100	0.061

Table 4.2 : MAE Values for Different Models till Epoch 200.

Model	Epoch	Value	Epoch	Value	Epoch	Value	Epoch	Value
Train	110	0.021	130	0.018	170	0.021	200	0.021
Test	110	0.062	130	0.063	170	0.063	200	0.062
Val	110	0.062	130	0.062	170	0.063	200	0.063

The MAE metric prefers lower values, and to prevent overfitting, it's essential to compare the MAE values of the training and validation sets. In this case, the best model was achieved at epoch 10 since the MAE values for both sets were relatively close. However, at epoch 30, the validation set's MAE was higher than the training set, indicating potential overfitting. This means that the model may have memorized the training data instead of learning transferable patterns that could be used on new data, resulting in superior performance on the training set compared to the validation set.

The MAE of the training and test sets is equal at epoch 10, after which they differ slightly. This is an indication that the model is performing well and able to generalize to new data. Generally, a small difference between the model's performance on the training and test sets or a small difference between the model's evaluation for overfitting on the train and validation sets is preferred as it suggests that the model is more likely to be able to generalize to new data.

4.3.2 Mean squared error

Another metric for pixel-to-pixel comparison is Mean Squared Error (MSE) (4.2), which is defined as follow:

Formula:

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(S(i,j)-G(i,j))^2 \tag{4.2}$$

where, $S(i,j)$ and $G(i,j)$ are the pixel values of the corresponding locations in the original and the reconstructed images, respectively. The summation is taken over M rows and N columns of the images.

4.3.3 Root mean square error

Additionaly, the Root Mean Square Error (RMSE) formula (4.3) for pixel-to-pixel comparison is given by:

Formula:

$$RMSE = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(S(i,j)-G(i,j))^2} \tag{4.3}$$

where M and N are the dimensions of the images, $S(i,j)$ is the pixel value of the reference image at location (i,j), and $G(i,j)$ is the pixel value of the image being evaluated at the same location.

The RMSE measures the average difference between the pixel values of two images, taking into account both the magnitude and the direction of the differences. It is commonly used as a measure of the overall similarity between two images.

The RMSE values for various epochs of the proposed model applied to OSMI Mental Health Image is shown in the tables (4.3) and (4.4).

Table 4.3 : RMSE Values for Different Models till Epoch 100.

Model	Epoch	Value	Epoch	Value	Epoch	Value	Epoch	Value
Train	10	0.143	30	0.091	70	0.097	100	0.087
Test	10	0.143	30	0.130	70	0.153	100	0.155
Val	10	0.142	30	0.129	70	0.152	100	0.152

Table 4.4 : RMSE Values for Different Models till Epoch 200.

Model	Epoch	Value	Epoch	Value	Epoch	Value	Epoch	Value
Train	110	0.087	130	0.082	170	0.088	200	0.089
Test	110	0.153	130	0.156	170	0.156	200	0.156
Val	110	0.153	130	0.153	170	0.155	200	0.155

A lower value of RMSE is preferred because it indicates that the model's predictions are more accurate. The interpretation of RMSE is similar to that of MAE. It is desirable to have a small difference between the model's performance on the training and test sets, or a small difference between the model's evaluation for overfitting on the train and validation sets, to avoid overfitting and ensure that the model can generalize well to new data.

4.3.4 Peak signal-to-noise ratio

The formula for PSNR (Peak Signal-to-Noise Ratio) (4.4) for pixel-to-pixel comparison is:

Formula:

$$PSNR = 10\log_{10}\left(\frac{MAX_I^2}{MSE}\right) \tag{4.4}$$

where MAX_I is the maximum possible pixel value of the image and MSE is the mean squared error between the original (source) image and the reconstructed(generated) image.

PSNR is a measure of the peak error between two images, expressed in decibels (dB). A higher PSNR value indicates a higher quality of the reconstructed image.

To calculate PSNR in practice, the two images (original and reconstructed) are first compared using MSE. Then, the resulting MSE value is plugged into the above formula to obtain the $PSNR$ value.

PSNR values for various epochs of the proposed model applied to OSMI Mental Health Image is presented in the table (4.5) and (4.6) as follow. A higher value for PSNR is acceptable, which implies that the reconstructed(generated) image is closer to the original(source) image in terms of pixel values.

Table 4.5 : PSNR Values for Different Models till Epoch 100.

Model	Epoch	Value	Epoch	Value	Epoch	Value	Epoch	Value
Train	10	65.3	30	69.6	70	68.5	100	69.4
Test	10	65.4	30	66.3	70	64.6	100	64.5
Val	10	65.4	30	66.3	70	64.7	100	4.6

Table 4.6 : PSNR Values for Different Models till Epoch 200.

Model	Epoch	Value	Epoch	Value	Epoch	Value	Epoch	Value
Train	110	69.5	130	69.9	170	69.3	200	69.3
Test	110	64.6	130	64.4	170	64.4	200	64.4
Val	110	64.6	130	64.6	170	64.5	200	64.5

By comparing the PSNR values between different epoch on the table (4.5) and (4.6), it is obvious that after epoch 30 till epoch 200, the PSNR value for all epoch has the same value around 65. It suggests that the model's performance is consistent over time and it is not improving further. In this case, the model has converged at epoch 30 successfully. So, by comparing PSNR values between the training set and validation or test set it can be understand that the model's generalization performance is good at epoch 30.

4.3.5 Structural similarity index measure

Structural Similarity Index Measure (SSIM) (4.5)for pixel-to-pixel comparison is:

Formula:

$$\text{SSIM}(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{4.5}$$

where x and y are the two images being compared, μ_x and μ_y are the means of the respective pixel values, σ_x and σ_y are the standard deviations, σ_{xy} is the covariance, and C_1 and C_2 are constants to stabilize the division in case of small variance.

SSIM is a measure of structural similarity between two images and ranges between -1 and 1, where 1 indicates perfect similarity and -1 indicates no similarity.

Tables (4.7) and (4.8) present the SSIM values obtained by applying the proposed model to the OSMI Mental Health Image for different epochs.

Table 4.7 : SSIM Values for Different Models till Epoch 100.

Model	Epoch	Value	Epoch	Value	Epoch	Value	Epoch	Value
Train	10	0.775	30	0.885	70	0.791	100	0.807
Test	10	0.777	30	0.841	70	0.718	100	0.720
Val	10	0.776	30	0.840	70	0.717	100	0.722

Table 4.8 : SSIM Values for Different Models till Epoch 200.

Model	Epoch	Value	Epoch	Value	Epoch	Value	Epoch	Value
Train	110	0.809	130	0.813	170	0.805	200	0.805
Test	110	0.722	130	0.716	170	0.717	200	0.717
Val	110	0.720	130	0.717	170	0.715	200	0.715

The analysis of the tables (4.7) and (4.8) for different epochs of proposed model suggests that a higher SSIM score is achieved at epoch 30, which is considered favorable as it implies a higher level of similarity between the compared images

4.3.6 Signal-to-reconstruction-error ratio

Signal-to-Reconstruction-Error Ratio (SRE) (4.6) in pixel-to-pixel comparison is calculated as below:

Formula:

$$SRE = 10\log_{10}\left(\frac{\sum_{i=1}^{M}\sum_{j=1}^{N} G(i,j)^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}(S(i,j)-G(i,j))^2}\right) \tag{4.6}$$

where M and N are the dimensions of the images, S is the original image, and G is the reconstructed image.

The SRE score is a measure of the quality of an image, based on how well its structure and features are preserved in a processed or generated version of the image. It measures the ratio of signal power to the power of the reconstruction error, expressed in decibels (dB).

Table 4.9 : SRE Values for Different Models till Epoch 100.

Model	Epoch	Value	Epoch	Value	Epoch	Value	Epoch	Value
Train	10	0.224	30	0.114	70	0.208	100	0.192
Test	10	0.222	30	0.158	70	0.281	100	0.279
Val	10	0.223	30	0.159	70	0.282	100	0.277

Table 4.10 : SRE Values for Different Models till Epoch 200.

Model	Epoch	Value	Epoch	Value	Epoch	Value	Epoch	Value
Train	110	0.190	130	0.186	170	0.194	200	0.194
Test	110	0.277	130	0.283	170	0.282	200	0.282
Val	110	0.279	130	0.282	170	0.284	200	0.284

The SRE values at various epochs were analyzed at tables (4.9) and (4.10), which it is found that epoch 30 had the best performance. In this case, a lower SRE value is preferable because it implies that the model is more efficient at reducing the number of non-zero elements in the output, which is desirable for achieving greater sparsity.

4.3.7 Universal image quality index

The Universal Image Quality Index (UIQ) is a measure of image quality that assesses the similarity between a reference image and a distorted image. It calculates the degree of structural similarity and luminance similarity between the two images.

The Universal Image Quality Index (UIQ) formula (4.7) is explained as below :

Formula:

$$UIQ = \frac{1}{N}\sum_{i=1}^{N}\frac{(2\mu_{I_i}\mu_{K_i}+c_1)(2\sigma_{I_iK_i}+c_2)}{(\mu_{I_i}^2+\mu_{K_i}^2+c_1)(\sigma_{I_i}^2+\sigma_{K_i}^2+c_2)} \tag{4.7}$$

where N is the number of pixels in the image, μ_{I_i} and μ_{K_i} are the means of the intensities of the corresponding pixels in the reference and distorted images, $\sigma_{I_i}^2$ and $\sigma_{K_i}^2$ are the variances of the intensities of the corresponding pixels in the reference and distorted images, and $\sigma_{I_iK_i}$ is the covariance of the intensities of the corresponding pixels in the reference and distorted images.

The constants c_1 and c_2 are used to avoid instability when the denominator is close to zero. They are typically set to $c_1 = (0.01L)^2$ and $c_2 = (0.03L)^2$, where L is the maximum pixel value (e.g., 255 for an 8-bit grayscale image). The UIQ score ranges from 0 to 1, with higher values indicating better image quality.

The UIQ values obtained by using the proposed model on the OSMI Mental Health Image for various epochs are presented in tables (4.11) and (4.12).

Table 4.11 : UIQ Values for Different Models till Epoch 100.

Model	Epoch	Value	Epoch	Value	Epoch	Value	Epoch	Value
Train	10	0.597	30	0.808	70	0.446	100	0.445
Test	10	0.597	30	0.784	70	0.438	100	0.437
Val	10	0.598	30	0.784	70	0.439	100	0.438

Table 4.12 : UIQ Values for Different Models till Epoch 200.

Model	Epoch	Value	Epoch	Value	Epoch	Value	Epoch	Value
Train	110	0.440	130	0.437	170	0.435	200	0.435
Test	110	0.432	130	0.429	170	0.427	200	0.427
Val	110	0.433	130	0.429	170	0.427	200	0.428

The Universal Image Quality Index (UIQ) ranges between 0 and 1, where a higher value indicates better image quality. So, it can be concluded that epoch 30 has the higher values among other epochs. It is important to consider the performance of the model on all three sets (train, test, validation) to ensure that the proposed model is able to generalize well to new data.

4.3.8 Spectral angle mapper

The Spectral Angle Mapper (SAM) is a measure used for spectral comparison of two images. It is used to compare the angle between two n-dimensional vectors, where n is the number of spectral bands in each image. The SAM value is calculated by taking the inverse cosine of the angle between the two vectors. It is a measure of the similarity of the spectral content of the two images, with a lower SAM value indicating a higher degree of similarity.

The SAM index ranges from 0 to 90 degrees, with 0 degrees indicating a perfect match between two spectra. The formula of SAM (4.8) is:

Formula:

$$SAM = \cos^{-1}\left(\frac{\sum_{i=1}^{n} S_i G_i}{\sqrt{\sum_{i=1}^{n} S_i^2}\sqrt{\sum_{i=1}^{n} G_i^2}}\right) \tag{4.8}$$

Table 4.13 : SAM Values for Different Models till Epoch 100.

Model	Epoch	Value	Epoch	Value	Epoch	Value	Epoch	Value
Train	10	0.174	30	0.110	70	0.118	100	0.106
Test	10	0.174	30	0.158	70	0.186	100	0.188
Val	10	0.173	30	0.157	70	0.185	100	0.185

Table 4.14 : SAM Values for Different Models till Epoch 200.

Model	Epoch	Value	Epoch	Value	Epoch	Value	Epoch	Value
Train	110	0.106	130	0.100	170	0.108	200	0.108
Test	110	0.186	130	0.189	170	0.190	200	0.189
Val	110	0.186	130	0.186	170	0.188	200	0.188

Tables (4.13) and (4.14) display the SAM values obtained for the proposed model applied to the OSMI Mental Health Image across different epochs and models. A lower value of SAM implies that the model's predictions are more accurate and closer to the ground truth, which is considered desirable. Therefore, selecting epoch 30 based on this criterion is a reasonable approach to avoid overfitting and achieve the best model.

4.4 Result Analysis

In this section, a visualization technique is utilized to compare and evaluate the performance of different models on various metrics including train, test, and validation data across different epochs. This technique involves generating a bar plot that shows the metrics and models, as well as a line graph with markers that displays the values for each epoch and model. Additionally, the maximum and minimum values for each metric across all epochs are identified and represented using dashed lines, and vertical lines are plotted at the epoch with the highest value for each metric.

By analyzing the position of the maximum and minimum lines in the plot for various models and metrics, it is possible to gain insight into the relative performance of different models. This analysis allows for the identification of the best model for a given metric, thus contributing to the advancement of the field by enabling more accurate and efficient model selection.

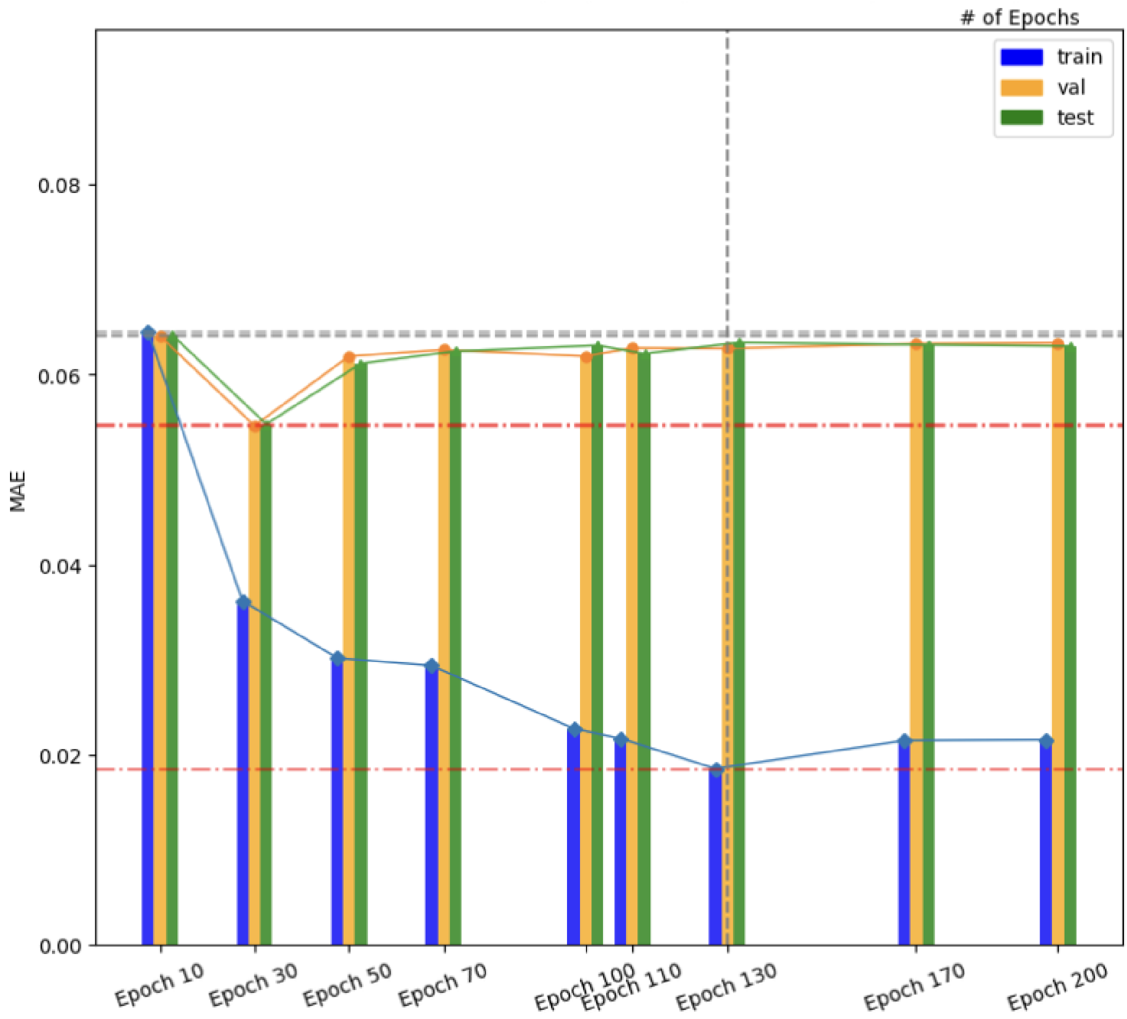

Figure 4.1 : MAE for Train, Test, and Validation at Different Epochs.

The MAE bar plot (4.1) for different models at various epochs indicates that epoch 30 can be considered as the one with the best performance on the MAE metric for the corresponding model, with the minimum line for MAE. Although there is a slight difference between the MAE for the train set and that of the test and validation sets, this difference is negligible. Beyond epoch 30, however, a significant difference is observed. At epoch 130, it can be observed that there is only one vertical line, indicating that the model's performance has reached a stable state and is experiencing minimal changes between epochs. This suggests that the model has likely converged to a point where further training might not yield significant improvements. However, it is crucial to carefully consider the specific context of the models being trained and the evaluation metrics employed to fully understand the implications of these observations.

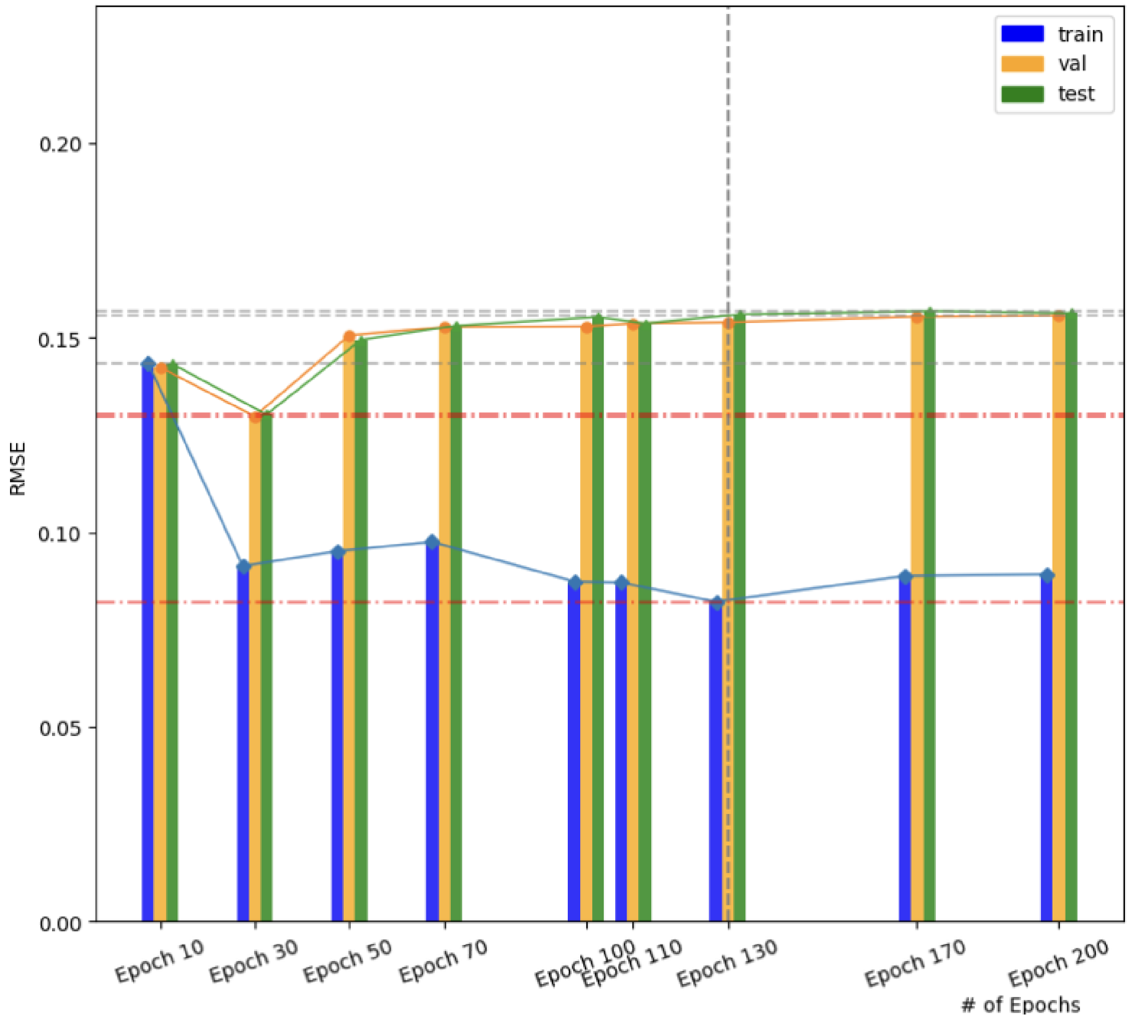

Figure 4.2 : RMSE for Train, Test, and Validation at Different Epochs.

The analysis from figure (4.2) reveals that the results obtained for RMSE are consistent with those for MAE, with epoch 30 exhibiting satisfactory performance for the train, test, and validation sets compared to other epochs. Despite the minor deviation in RMSE between the training and validation sets, which could suggest overfitting, this disparity can be disregarded when considering the other metrics for evaluation, which would be presented in the following of study.

In epoch 130, it becomes evident that the model has reached a state of stability where its performance remains consistent with minimal variations observed between epochs.

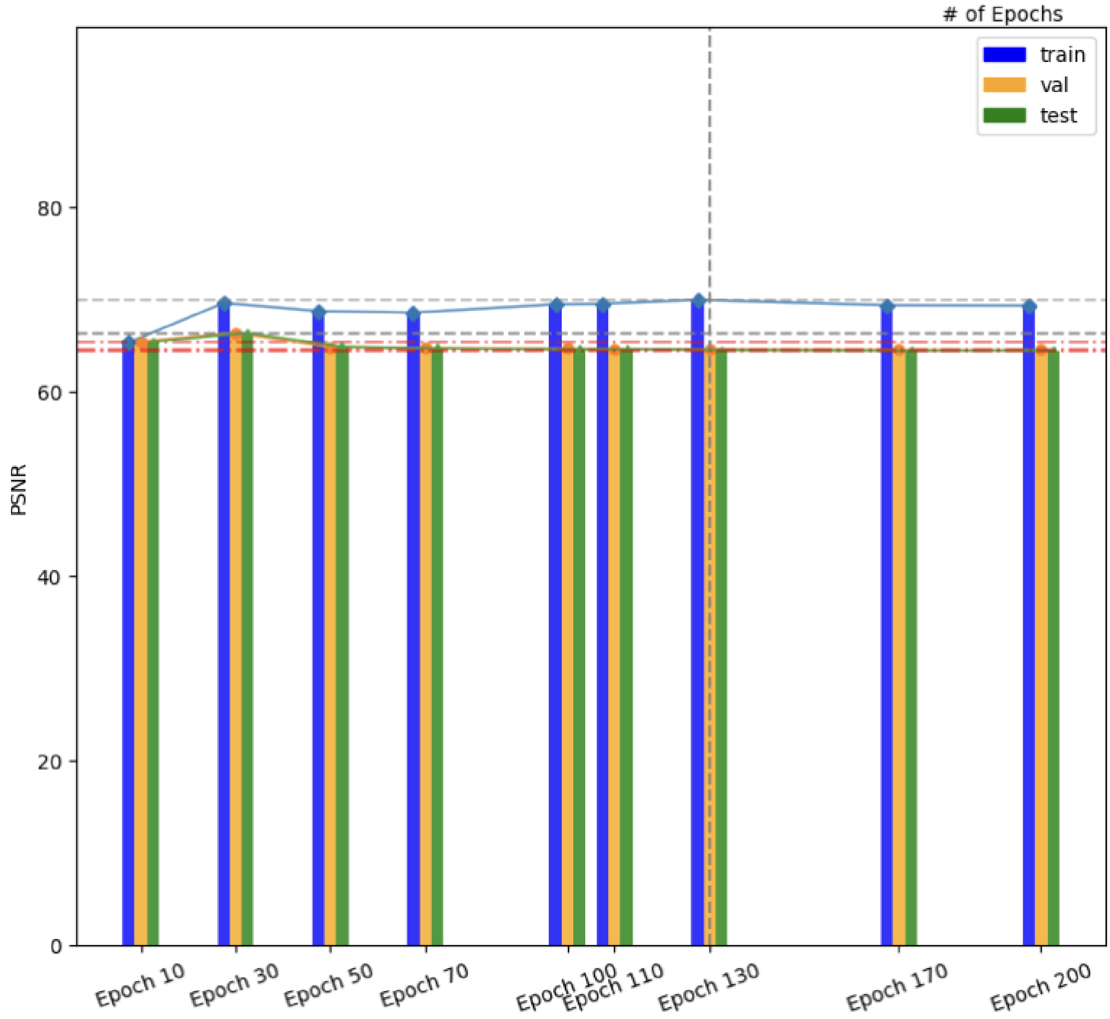

Figure 4.3 : PSNR for Train, Test, and Validation at Different Epochs.

As mentioned in subsequent discussions, a higher PSNR value indicates better image quality. It can be inferred from the figure (4.3) that the PSNR at epoch 30 is optimal with the highest among different models.

Therefore, by assessing the Peak Signal-to-Noise Ratio (PSNR), it becomes feasible to assess the quality of reconstructed or compressed images, and identify the most suitable model at epoch 30. In epoch 130, it becomes apparent that the model has attained a stable state where its performance shows little fluctuation or change across subsequent epochs.

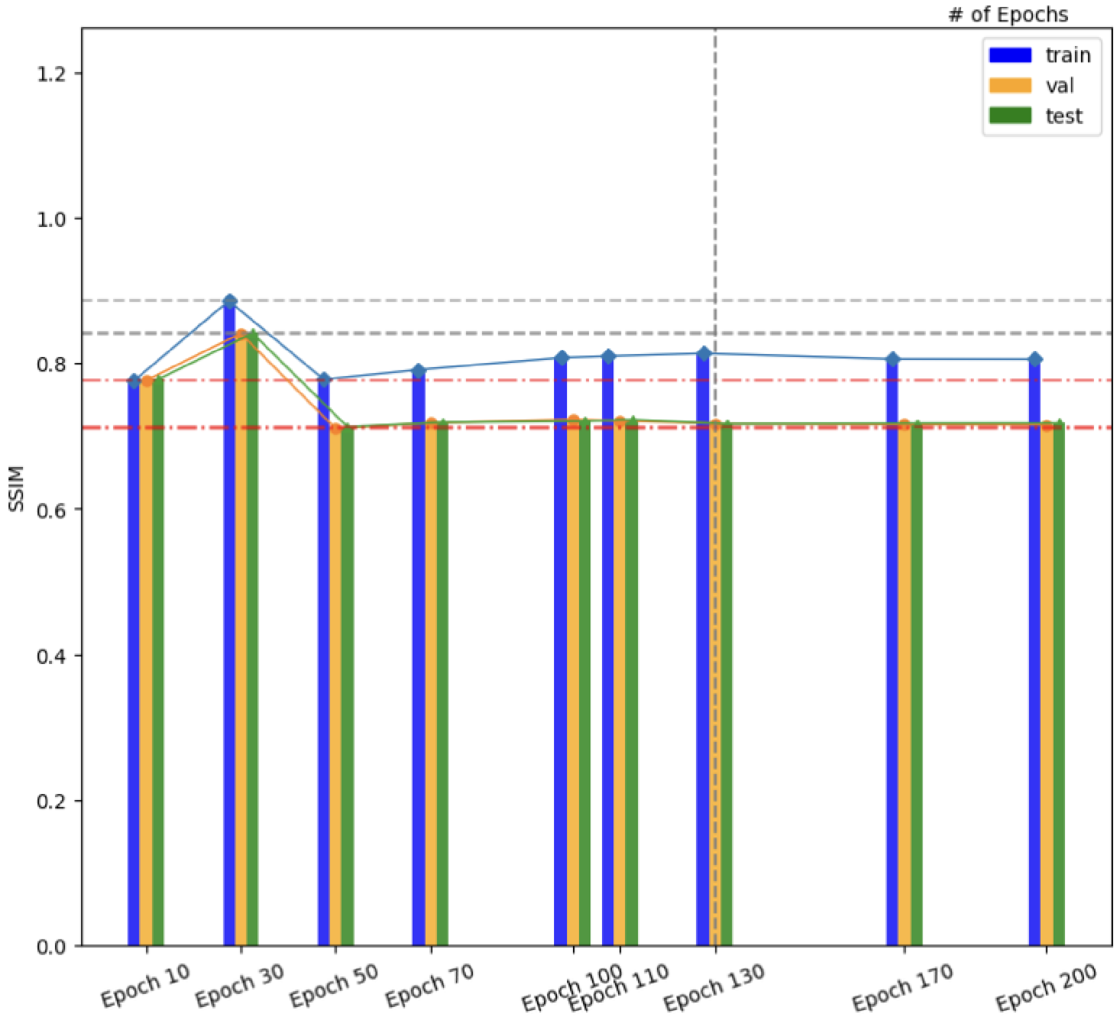

Figure 4.4 : SSIM for Train, Test, and Validation at Different Epochs.

The figure (4.4) presents the analysis of SSIM (Structural Similarity Index Measure), which considers the luminance, contrast, and structure of images to evaluate the performance of different models on train, test, and validation sets at different epochs. It is evident from the plot (4.4) that the model at epoch 30 has the best performance, with the highest SSIM value close to 1 indicating high similarity between images and minimal difference between train, test, and validation sets to avoid overfitting. However, after epoch 30, this difference gradually increases with each epoch. Therefore, the model at epoch 30 can be considered the best model based on the SSIM metric. By epoch 130, it becomes apparent that the model's performance has stabilized, exhibiting minimal fluctuations between successive epochs.

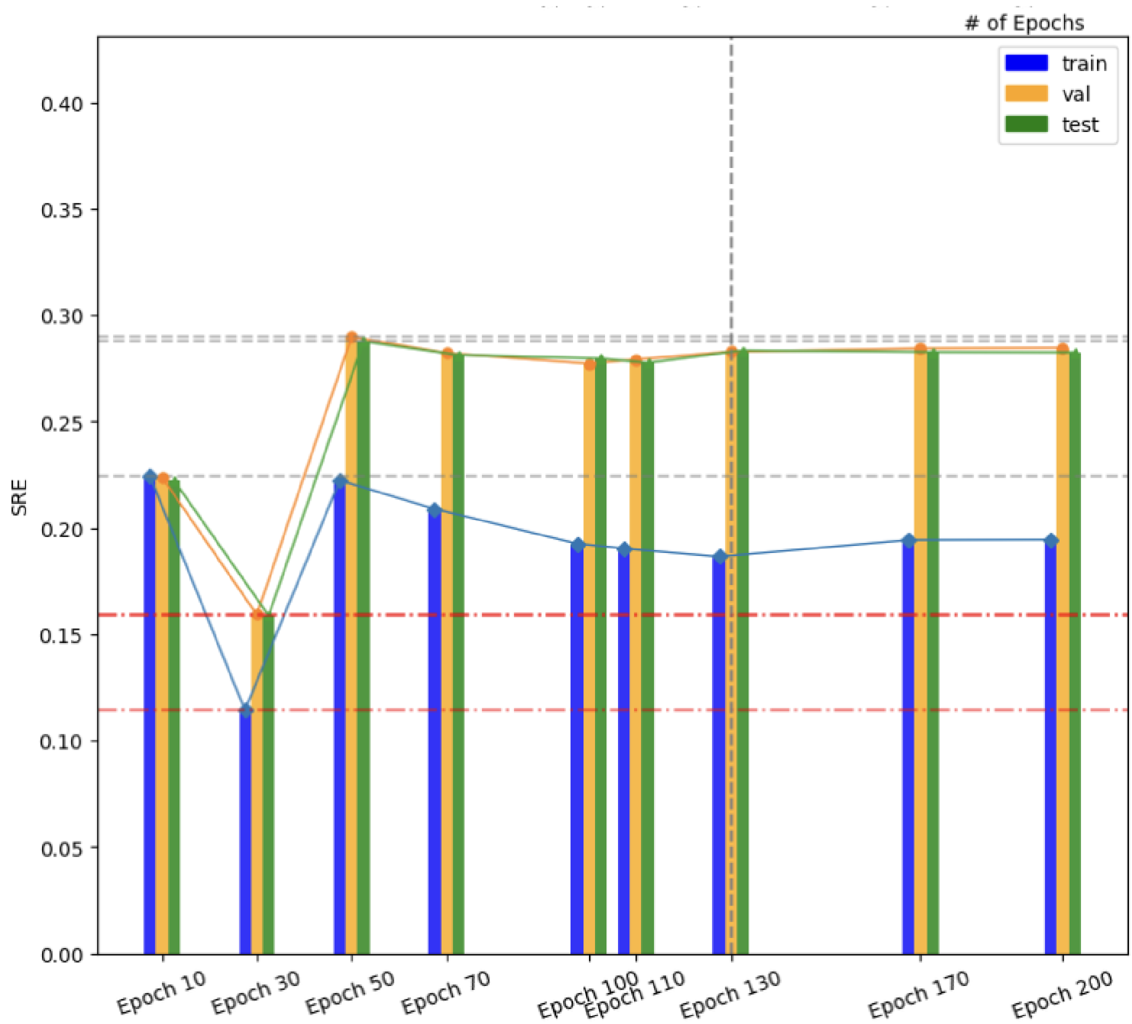

Figure 4.5 : SRE for Train, Test, and Validation at Different Epochs.

The bar plotted graph in figure (4.5) shows that epoch 30 has the lowest SRE values across all three models, indicating a superior quality of signal reconstruction. This is because the smaller the difference between the original signal and the reconstructed signal, the better the reconstruction quality. At epoch 130, it is evident that the model's performance has reached a point of stability, with negligible changes observed between subsequent epochs.

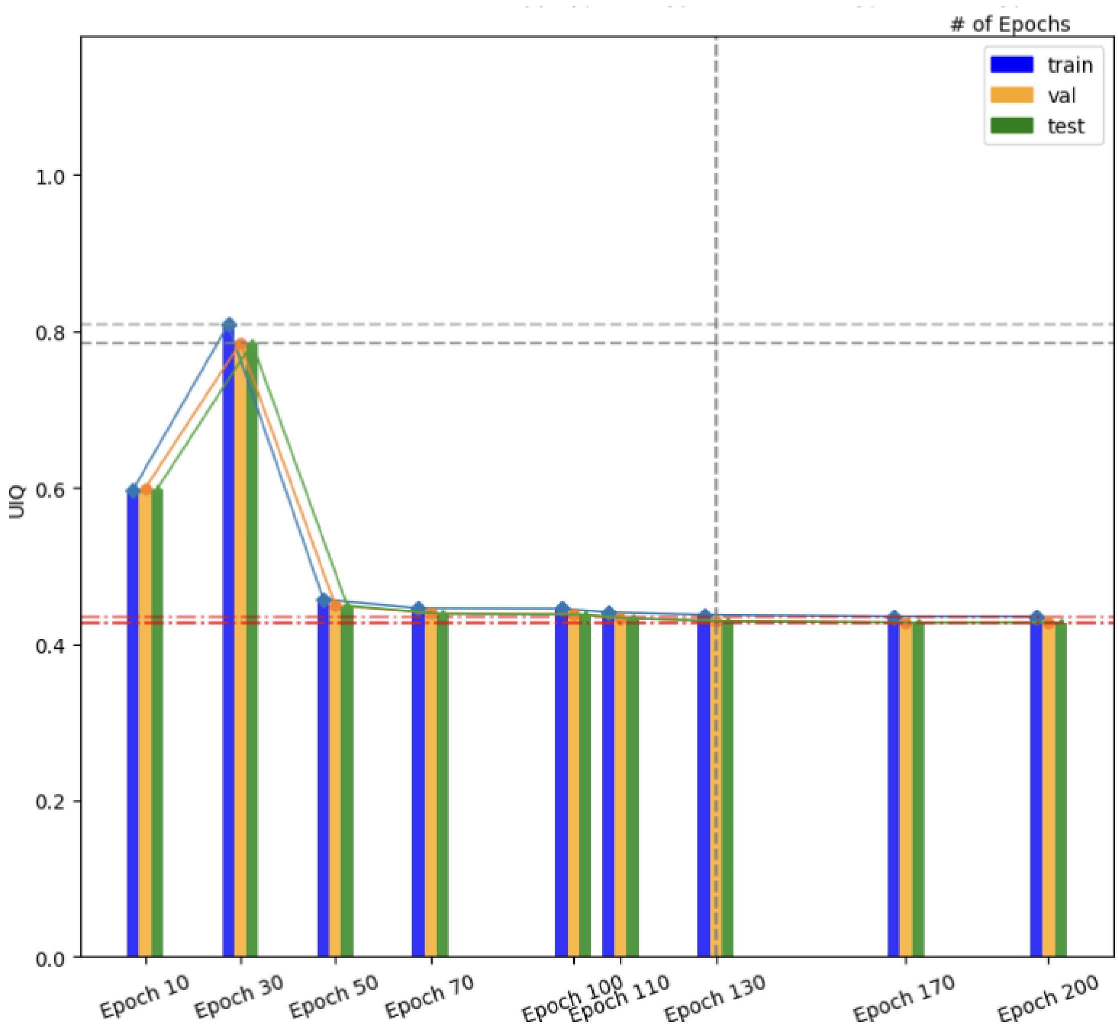

Figure 4.6 : UIQ for Train, Test, and Validation at Different Epochs.

The UIQ is a metric that considers several factors such as luminance, contrast, and structure to measure the overall quality of an image. A higher UIQ value implies better image quality. From the results (4.6), it is evident that epoch 30 performs exceptionally well for all three models and achieves the highest UIQ value. In epoch 130, it can be observed that the model's performance has reached a stable state, characterized by minimal variations or fluctuations between consecutive epochs.

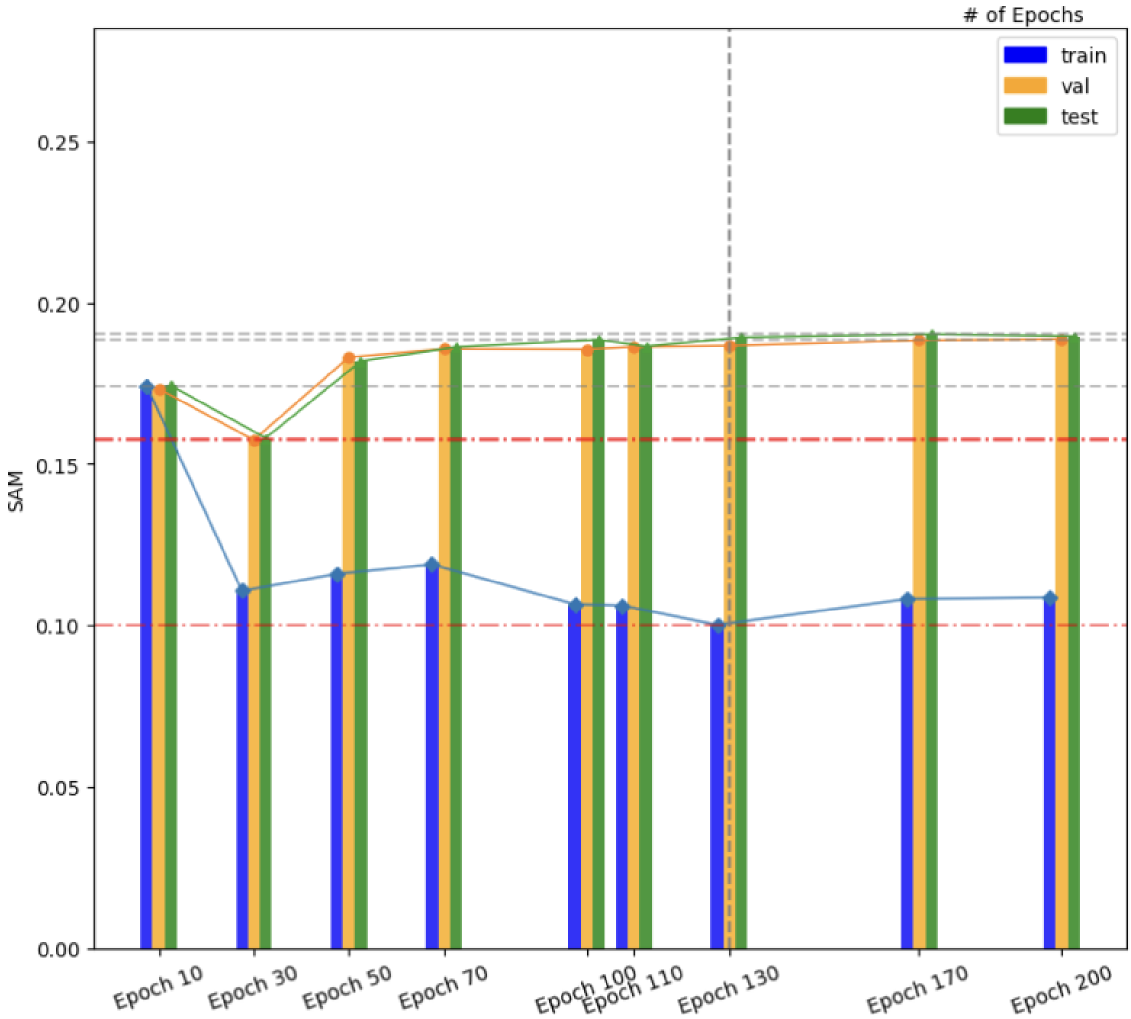

Figure 4.7 : SAM for Train, Test, and Validation at Different Epochs.

The SAM (Spectral Angle Mapper) metric measures the similarity between two images, with lower values indicating higher similarity. The results of SAM from figure (4.7) for epoch 30 of all three models show small differences between them, indicating a high level of similarity. These results further support the decision to select epoch 30 as the best model. At epoch 130, it is evident that the model's performance has stabilized, with minimal discernible changes occurring between successive epochs.

4.5 Generated Images and Pix2pix GAN Model's Predicted Results

4.5.1 Train images

The task of generating image descriptions has been an essential aspect of computer vision. However, evaluating and comparing the performance of GANs models and the images they generate is challenging. This is primarily due to the absence of an explicit likelihood measure [151], which is commonly used in comparable probabilistic models [152]. As a result, previous studies have mainly relied on subjective visual evaluations to assess the quality of images synthesized by GANs. In this study, image illustrations are used to demonstrate how the quality of the generated images improves over the course of training on a dataset of 932 images, with a random image, numbered 616, to demonstrate the improvement as epoch increases up to 200. Although visual inspection is helpful in understanding how the GAN learns and how to enhance its performance, it is not sufficient to determine the best model or epoch. Other factors, such as metric evaluation using quantitative measures like MSE, RMSE, PSNR, SSIM, and UIQ, need to be considered. It is also essential to analyze the performance differences between the training, validation, and testing sets and assess the risk of overfitting. Combining these factors can lead to a more informed decision regarding the best model and epoch for the proposed pix2pix GAN model in this study. The figures (4.8), (4.9), (4.10), and (4.11) display the trained image sample number 616 at different epochs, specifically at epochs 10, 30, 100, and 200, respectively. Moreover, a table (4.15) presenting the evaluation metrics for image number 616 has been depicted as shown below.

Table 4.15 : Metric Evaluation Results for Trained Image Number 616 at Different Epochs.

Epoch	RMSE	MAE	PSNR	SSIM	SRE	SAM	UIQ
10	0.0712	0.028	71.07	0.843	0.156	0.09	0.617
30	0.063	0.025	72.04	0.903	0.096	0.081	0.829
100	0.080	0.020	70	0.812	0.187	0.102	0.444
200	0.076	0.016	70.46	0.817	0.182	0.096	0.434

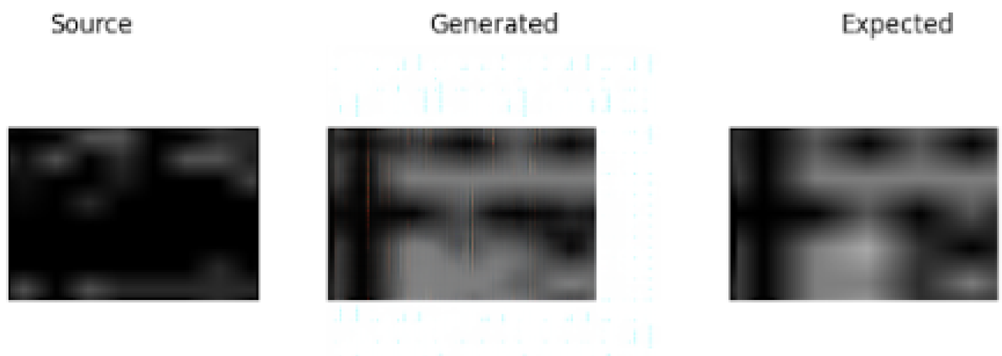

Figure 4.8 : Trained Image for Epoch=10.

Figure 4.9 : Trained Image for Epoch=30.

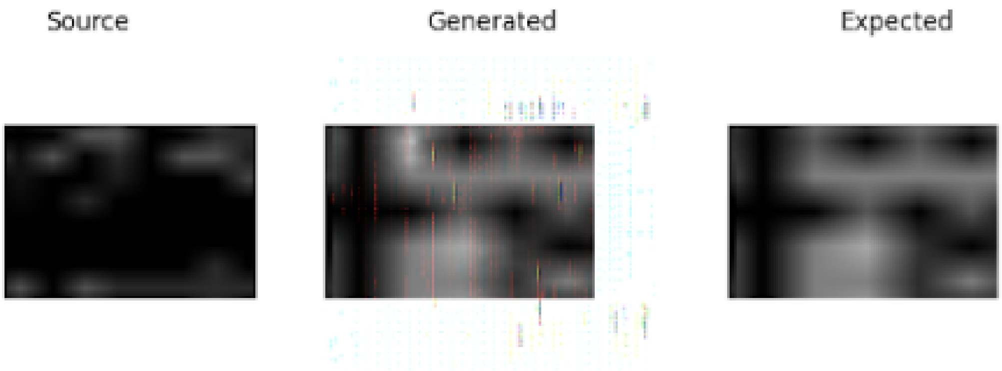

Figure 4.10 : Trained Image for Epoch=100.

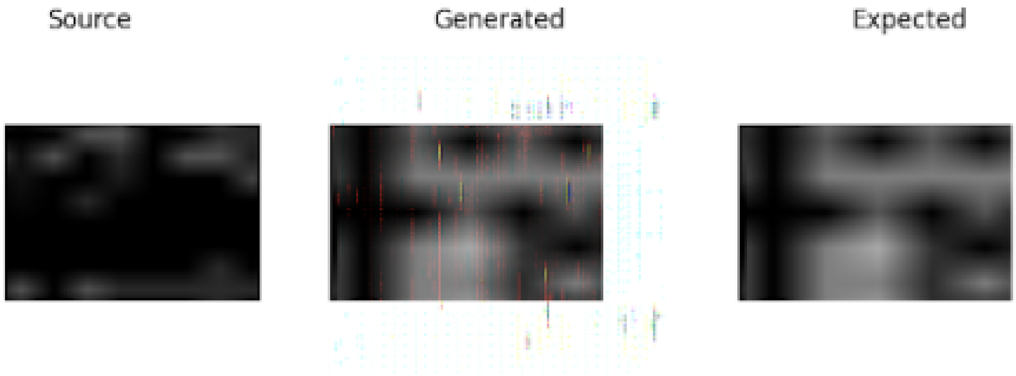

Figure 4.11 : Trained Image for Epoch=200.

After visually comparing image number 616 at different epochs and analyzing the metric evaluation results, it has been determined that epoch 30 produced the most favorable results for this image. The evaluation metrics for epoch 30 and image number 616 are as follows: RMSE = 0.063, MAE = 0.025, PSNR = 72.04, SSIM = 0.903, SRE = 0.096, SAM = 0.081, and UIQ = 0.829. These results indicate that the image quality is good, as all favorable metrics are satisfied, including lower RMSE, MAE, SRE, SAM, and higher PSNR, SSIM, and UIQ. Therefore, based on the evaluation metrics and visual inspection, epoch 30 can be considered as the best epoch for this specific image.

4.5.2 Test images

This section presents a sample test image, number 177, for detailed visualization. Before training the pix2pix GAN model, 292 images were split for testing. The generated output images at different epochs were compared with the ground truth (target) images, and quantitative metrics such as Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Universal Image Quality Index (UIQ) were used to choose the best epoch that gives the best performance on the test images. Based on these metrics and visual inspection, epoch 30 was selected as the best model for image number 177, with RMSE = 0.048, MAE = 0.019, PSNR = 74.38, SSIM = 0.914, SRE = 0.085, SAM = 0.061, and UIQ = 0.837, which met all the requirements for selecting the best model. The figures (4.12), (4.13), (4.14),and (4.15) are displayed below, along with the corresponding metric table (4.16).

Table 4.16 : Metric Evaluation Results for Tested Image Number 177 at Different Epochs.

Epoch	RMSE	MAE	PSNR	SSIM	SRE	SAM	UIQ
10	0.082	0.037	69.82	0.816	0.183	0.104	0.606
30	0.048	0.019	74.38	0.914	0.085	0.061	0.837
100	0.098	0.033	68.21	0.767	0.232	0.125	0.437
200	0.085	0.022	69.47	0.786	0.213	0.108	0.425

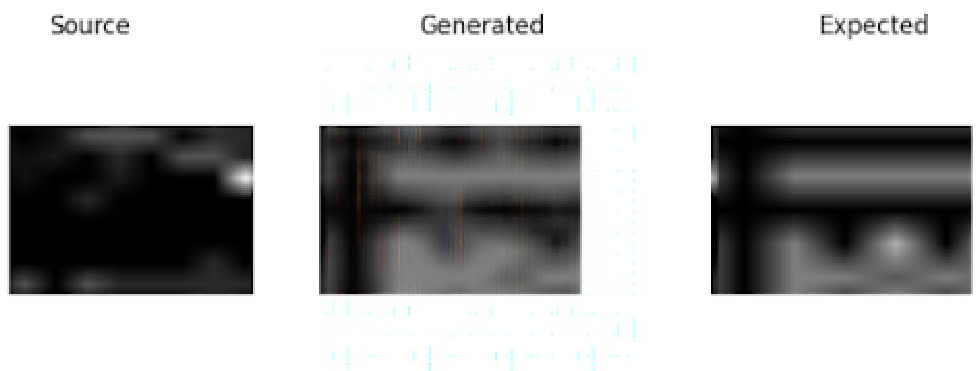

Figure 4.12 : Tested Image for Epoch=10.

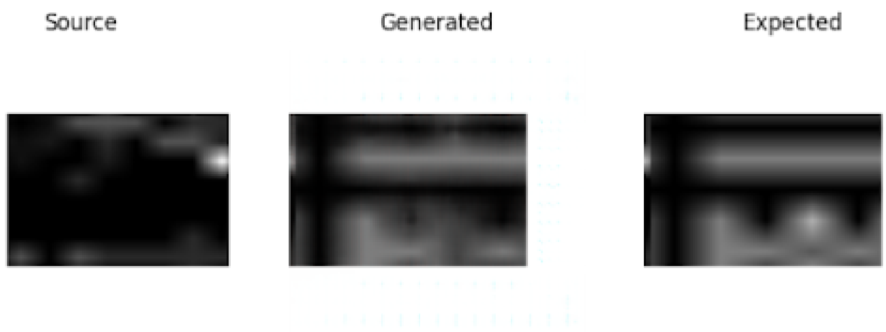

Figure 4.13 : Tested Image for Epoch=30.

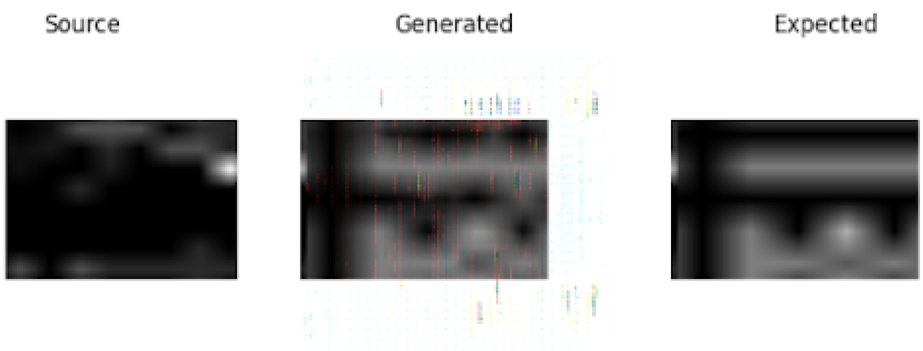

Figure 4.14 : Tested Image for Epoch=100.

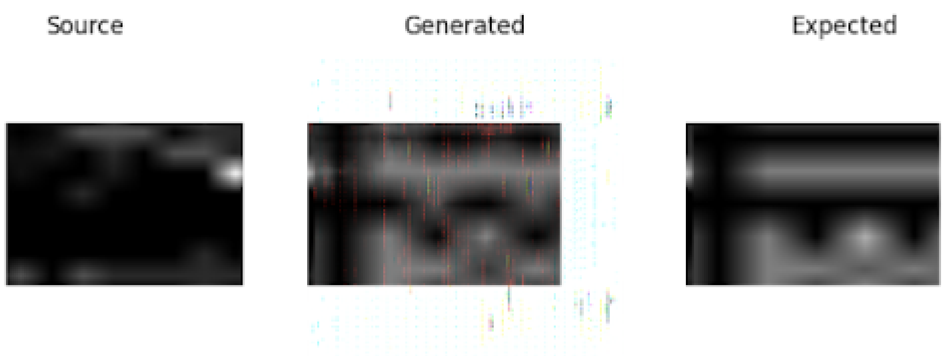

Figure 4.15 : Tested Image for Epoch=200.

4.5.3 Validation images

For the validation set, 234 images were split and one image, number 118, was selected for visual inspection. The figures (4.16), (4.17), (4.18), and (4.19) show the generated output images at different epochs, which were compared to the ground truth image (target image) to evaluate the model's performance. The quantitative metrics used for evaluation were Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Universal Image Quality Index (UIQ), and the results are presented in a table (4.17) for more clarity. After analyzing both the visual and quantitative metrics, epoch 30 with RMSE = 0.049, MAE = 0.020, PSNR = 74.31, SSIM = 0.914, SRE = 0.085, SAM = 0.0615, and UIQ = 0.836 was found to have the highest similarity and optimal results for this specific image.

Table 4.17 : Metric Evaluation Results for Validation Image Number 118 at Different Epochs.

Epoch	RMSE	MAE	PSNR	SSIM	SRE	SAM	UIQ
10	0.099	0.039	68.13	0.826	0.173	0.124	0.619
30	0.049	0.020	74.31	0.914	0.085	0.0615	0.836
100	0.087	0.026	69.29	0.797	0.202	0.110	0.442
200	0.090	0.030	69.02	0.781	0.218	0.113	0.431

The images are created by the generated model and the target images for image 118 are presented on the next page, which allows for a comparison of the images at each epoch.

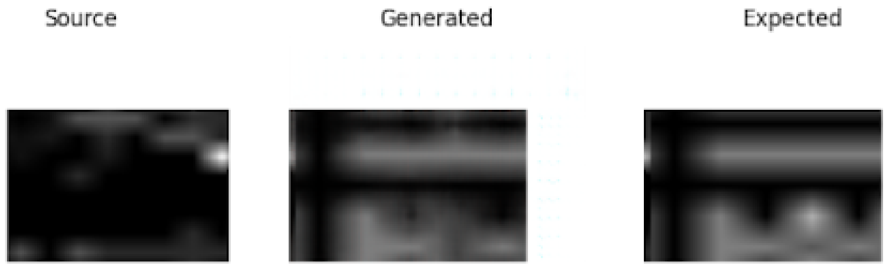

Figure 4.16 : Validation Image for Epoch=10.

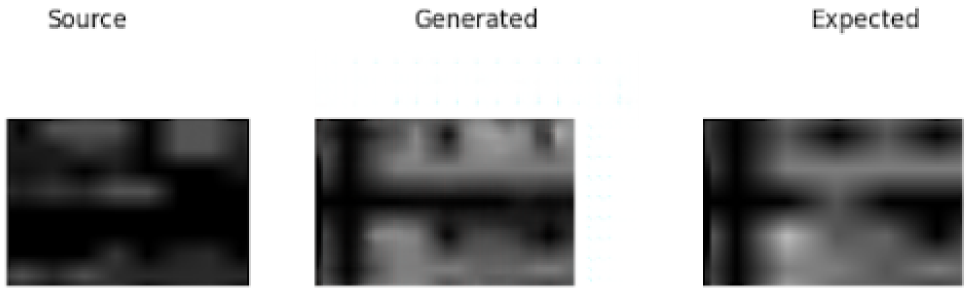

Figure 4.17 : Validation Image for Epoch=30.

By examining the generated and target images at both epoch 10 and epoch 30 (4.16), (4.17), it is possible to evaluate the degree of similarity between them. However, it is important to take into account additional evaluation metrics in order to fully assess the similarity between the images.

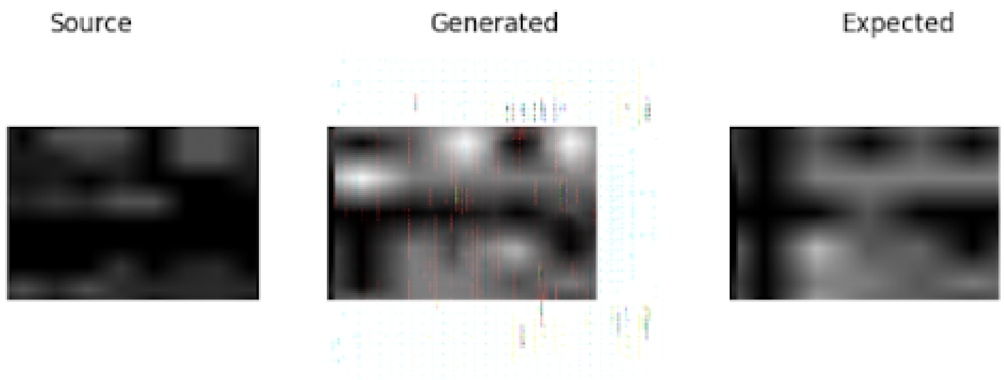

Figure 4.18 : Validation Image for Epoch=100.

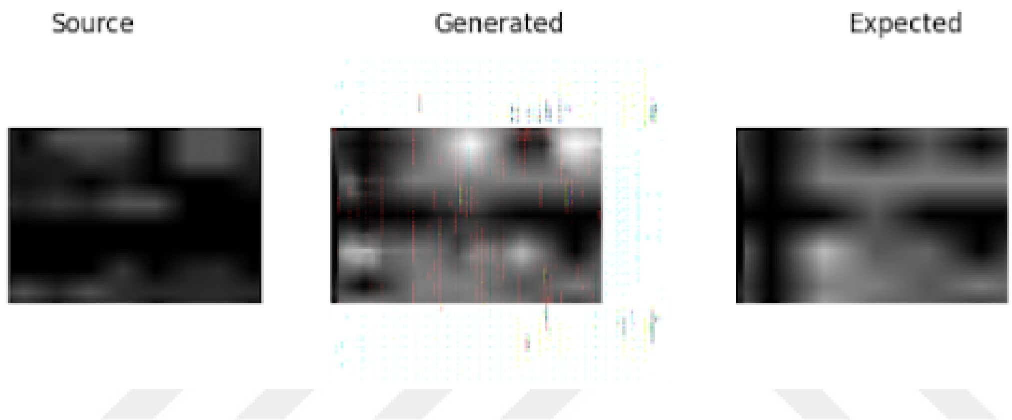

Figure 4.19 : Validation Image for Epoch=200.

4.5.4 Summary of obtained results

In conclusion, the results of evaluating the pix2pix GAN model on a dataset of 1458 images using quantitative metrics and visual inspection show that the model was successful in generating high-quality images. To avoid overfitting, the dataset was divided into train, test, and validation sets, and the model was evaluated based on its performance on each set.

Epoch 30 is found to be the optimal epoch for all sets, indicating that this was the best hyperparameter setting for the model. Moreover, by capitalizing on the learning process between the features and labels across the entire training dataset, valuable patterns were extracted. These extracted patterns, observed at various levels of detail, contribute to a more comprehensive understanding and facilitate insightful learning. As a result, the generated images exhibit high performance. Overall, the results indicate that the pix2pix GAN model is a useful tool for producing high-quality images for creating MHI (Mental Health Images), which could potentially have a novel application in detecting valuable information in today's world.

Furthermore, there are several factors that may explain why epoch 30 is the optimal point for the model's performance. One possible explanation is that the model is able to learn float values more efficiently than actual images, resulting in faster learning and better performance. Another possibility is that the architecture and hyperparameters of the model, as well as the optimization algorithm used during training, play a critical role in achieving optimal performance in GANs. These factors are crucial components of GAN architecture and can greatly affect the model's performance.

4.6 Extracting Information from Generated Visual Images

This section showcases fascinating insights that can be further explored by analyzing the images. As explained earlier, the study converted responses to mental health disorder questions in the Tech Survey into floating point numbers, then used them to create feature and label pixel images by assigning each answer to a pixel. The final step involved training a pix2pix GAN to generate images based on these selected features and labels.

Now, the study seeks to interpret the colors of the generated pixel images. The meaning of colors in an image depends on the color space used. Typically, images use the RGB color space, which combines red, green, and blue channels, with each pixel having a value for each channel ranging from 0 to 255. The combination of these values determines the color of the pixel. In this research, the feature and label pixel images created from responses to mental health disorder questions represent the intensity or value of each pixel, rather than the color. During training, the pix2pix GAN learns to map the input feature image to the output label image and generates a color image based on this mapping. This is an interesting aspect of the research, as analyzing the intensity or value of each pixel in the feature and label images can provide more valuable information.

To map the feature and label images for a mental health image dataset, a clear correspondence between the two is necessary. As described in section (3.2.2), previous research on OSMI indicated that five labels were crucial in determining whether an employee was suffering from a mental health disorder or not. Therefore, to interpret the changing colors of pixels, these five labels, which is shown by star in the pictures (L7, L9, L11, L17, L20), are given priority.

Upon analyzing various images and comparing the feature pixel images (4.20) and the generated pixel images (4.21) from the GAN with the target pixel images (4.22) for each employee, it was observed that there is a significant relationship between individuals who discuss their mental health with a potential employer during an interview (L20), mental health disorders that interfer their work (L17), and individuals with a family history of mental illness (F53), along with other corresponding responses.

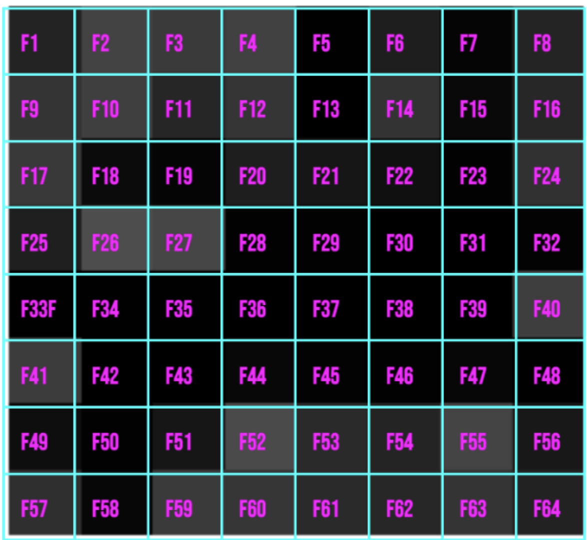

Figure 4.20 : Feature Image.

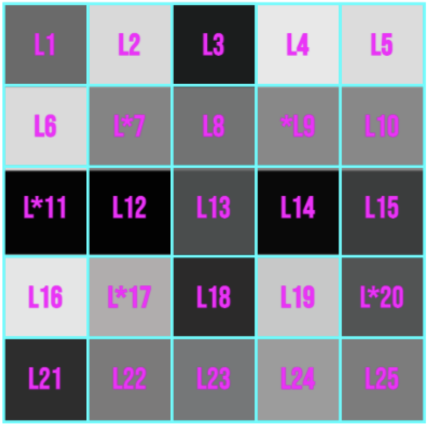

Figure 4.21 : Generated Image.

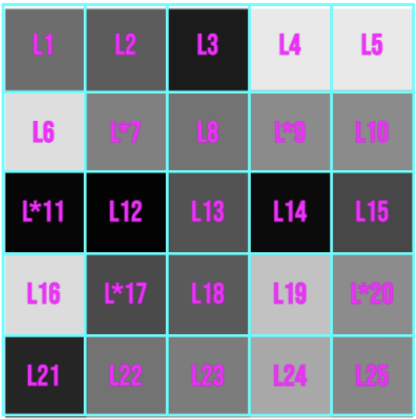

Figure 4.22 : Target Image.

Moreover, this study discovered that based on Patel [153] study, mental health disorders that interfere with work (L17), family history of mental illness (F53), gender (F56), and previous employers' provision of mental health benefits (L16) are interconnected. Furthermore, Modupe et al. [154] indicated an association between employees' family history (F53), gender (F56), and the medical coverage available in the workplace (F12), which is approved by this study.

Upon comparing the target images and generated images, it was observed that the colors of two labels (L17, L20) associated with questions regarding mental health disorders and their impact on employees' work and willingness to bring up mental health during an interview with a potential employer vary more. This variation could be attributed to several factors such as the complexity of the questions, the features associated with the labels, or the diversity in responses to those questions. It's possible that the GAN model struggles to generate a consistent color for those labels because of the broad range of input features that correspond to those labels. In other words, the model may be attempting to capture too many different variations in the input features, making it difficult to generate a uniform color for those labels. Another possible explanation could be that the GAN model has not yet converged, or there may be issues with the training data or model architecture that are causing the problem.

By analyzing the patterns and distributions of pixel colors, the research gained insights into the connections between mental health features and their corresponding labels or symptoms. This information is vital for human resource departments to create an environment that promotes productivity at work because a diagnosis of a mental health disorder does not necessarily mean that a person cannot be productive or valuable in the workplace.

4.7 Discussion

The pix2pix GAN technique is a highly beneficial approach for improving both artificial and real images, and this is likely due to the strong generator network it employs. The generator uses a U-net architecture with skip connections to produce high-quality images, and the PatchGAN discriminator allows for effective local analysis of image patches, resulting in more coherent generated images. Additionally, the L1 distance loss function used during training enhances the sharpness and clarity of the generated images. When combined, these factors lead to the superior performance of Pix2Pix GAN in image enhancement tasks. Furthermore, this innovative approach has the potential to expand the use of this model to clinical and acute care settings.

Based on the results of the pix2pix GAN model, which achieved its best performance at epoch 30, there are many possible reasons for why this occurred. One explanation is that the choice of float values versus actual images may have played a role in the model's performance at epoch 30. Another possibility is that the specific images used in the dataset may have been better suited to the model architecture and hyperparameters at epoch 30. These findings are important because they suggest that achieving good model performance at a lower epoch number is desirable since it indicates that the model can learn and generalize quickly without requiring an excessive amount of training. Additionally, having a model that performs well at a lower epoch number can save computational resources and time during training. These results are relevant for researchers and practitioners working in the field of deep learning and image processing, as they highlight the importance of selecting appropriate hyperparameters and datasets to optimize model performance. Overall, these findings contribute to our understanding of how to improve the performance of GAN models and provide insight into the factors that contribute to their success.

Another important topic to discuss is the reason behind converting a (5x5) label image pixel that contains questions to a (256x256) image pixel. This was done not only because it is necessary for the pix2pix GAN entrance but also because the aim of this research is to see the details more clearly. The size of the image can greatly impact the quality and detail of the information contained within the image, and a (5x5) pixel image may not be sufficient to capture all necessary details for the project or analysis.

By increasing the image size to (256x256) pixels, the resolution is effectively increased, allowing for greater detail to be captured and potentially improving the accuracy and quality of the analysis. Additionally, the larger size may be necessary for the pix2pix GAN model to properly process and analyze the image, as it is designed to work with images of a certain size and resolution. Therefore, increasing the image size can improve the quality of the analysis and ensure proper formatting for use with the Pix2Pix GAN model.

5. CONCLUSION

This work introduces a novel approach using the pix2pix GAN algorithm to create a mental health picture of employees by using OSMI dataset. This approach leverages deep learning and neural networks to develop a more sophisticated tool for future research. The result is a fast, simple, effective, and reliable way for HR employees to evaluate current or prospective workers. By demonstrating the feasibility of using pix2pix for psychotropic image generation, this study explores the potential of this method for this particular application.

The pix2pix GAN shows the ability to learn patterns and relationships between input images and corresponding output images. In the context of mental health, this means that the model can learn from a dataset of images related to mental health conditions or indicators. By training the pix2pix GAN on a dataset that includes both input images (such as medical images, behavioral observations, or self-reported symptoms) and corresponding output images (such as diagnosed mental health conditions or labels indicating mental health states), the model can learn to generate or predict mental health images based on given input information.

This predictive capability of the pix2pix GAN can be valuable for human resource professionals. It can potentially assist them in identifying or predicting mental health conditions in employees based on available data. This can ease the job of human resource professionals by providing an additional tool to support their decision-making process and enable early intervention or targeted support for employees' mental well-being.

5.1 Limitation

There are some potential limitations in this research, which can be highlighted as follows. Pix2pix GAN requires paired data, which includes an input image and a corresponding target output image, to train the model. This means that both the features and labels need to be present in the data, which can be a limitation in certain applications where obtaining paired data is difficult or expensive.

Another limitation is the requirement of powerful GPUs and computational resources when using the pix2pix GAN for generating individual mental health images. The model's accessibility and scalability also restricted by this limitation somehow.

5.2 Future Research

In future research, it is highly recommended to explore the application of other types of GANs, such as CycleGAN, to generate images from OSMI data. This is particularly relevant as CycleGAN was developed to overcome the limitation of pix2pix, which requires paired data for training. Deep Learning methods have shown great promise in numerous medical diagnostic applications and have even demonstrated superior performance compared to human experts in certain cases. Hence, it would be advantageous to utilize these tools in practical settings that have a significant impact on people's lives.

Furthermore, this research has the potential to challenge the prevailing notion that mental health disorders invariably result in reduced productivity. By enabling faster diagnosis and treatment through the use of predictive models like the pix2pix GAN, employers can take proactive measures to support employees' mental well-being. Additionally, individuals themselves may become more conscious of their mental health, leading to increased awareness and self-care. This opens up avenues for more comprehensive studies in the future, examining the impact of such advancements on mental health outcomes and productivity in the workplace.

REFERENCES

[1] **Rehm, J. and Shield, K.D.** (2019). Global burden of disease and the impact of mental and addictive disorders, *Current psychiatry reports*, *21*(2), 1–7.

[2] **Bloom, D.E.**, **Cafiero, E.**, **Jané-Llopis, E.**, **Abrahams-Gessel, S.**, **Bloom, L.R.**, **Fathima, S.**, **Feigl, A.B.**, **Gaziano, T.**, **Hamandi, A.**, **Mowafi, M.** *et al.* (2012). The global economic burden of noncommunicable diseases, **Technical Report**, Program on the Global Demography of Aging.

[3] **Fattah, H.A.**, **Hasan, K.A. and Das, S.** (2021). A Voting Classifier for the Treatment of Employees' Mental Health Disorder, *2021 International Conference on Automation, Control and Mechatronics for Industry 4.0 (ACMI)*, IEEE, pp.1–6.

[4] **Delusions, C.P.O.** (2015). WPA, *World Psychiatry*, *14*, 119–136.

[5] **Appiah, S.**, **Barnard, S. and Deiven, J.** (2017). *Density-based Clustering of Workplace Effects on Mental Health*.

[6] **Leka, S.**, **Jain, A.**, **Organization, W.H.** *et al.* (2010). Health impact of psychosocial hazards at work: an overview.

[7] **Atilola, O.** (2012). Partaking in the global movement for occupational mental health: what challenges and ways forward for sub-Sahara Africa?, *International Journal of Mental Health Systems*, *6*(1), 1–10.

[8] **Sujal, B.**, **Neelima, K.**, **Deepanjali, C.**, **Bhuvanashree, P.**, **Duraipandian, K.**, **Rajan, S. and Sathiyanarayanan, M.** (2022). Mental Health Analysis of Employees using Machine Learning Techniques, *2022 14th International Conference on COMmunication Systems & NETworkS (COMSNETS)*, IEEE, pp.1–6.

[9] **Harvey, S.B.**, **Modini, M.**, **Joyce, S.**, **Milligan-Saville, J.S.**, **Tan, L.**, **Mykletun, A.**, **Bryant, R.A.**, **Christensen, H. and Mitchell, P.B.** (2017). Can work make you mentally ill? A systematic meta-review of work-related risk factors for common mental health problems, *Occupational and environmental medicine*, *74*(4), 301–310.

[10] **Brunner, B.**, **Igic, I.**, **Keller, A.C. and Wieser, S.** (2019). Who gains the most from improving working conditions? Health-related absenteeism and presenteeism due to stress at work, *The European Journal of Health Economics*, *20*(8), 1165–1180.

[11] **Nisar, S.K. and Rasheed, M.I.** (2020). Stress and performance: Investigating relationship between occupational stress, career satisfaction, and job performance of police employees, *Journal of Public Affairs*, *20*(1), e1986.

[12] **Harnois, G. and Gabriel, P.** (2000). Mental health and work: Impact, issues and good practices.

[13] **Johnson, S.**, **Cooper, C.**, **Cartwright, S.**, **Donald, I.**, **Taylor, P. and Millet, C.** (2005). The experience of work-related stress across occupations, *Journal of managerial psychology*.

[14] **Shockey, T.M.**, **Zack, M. and Sussell, A.** (2017). Health-related quality of life among US workers: Variability across occupation groups, *American journal of public health*, *107*(8), 1316–1323.

[15] **Landsbergis, P.A.**, **Schnall, P.L.**, **Deitz, D.K.**, **Warren, K.**, **Pickering, T.G. and Schwartz, J.E.** (1998). Job strain and health behaviors: results of a prospective study, *American journal of Health promotion*, *12*(4), 237–245.

[16] **Joyce, T.**, **McMillan, M. and Hazelton, M.** (2009). The workplace and nurses with a mental illness, *International Journal of Mental Health Nursing*, *18*(6), 391–397.

[17] **Brohan, E.**, **Henderson, C.**, **Little, K. and Thornicroft, G.** (2010). Employees with mental health problems: Survey of UK employers' knowledge, attitudes and workplace practices, *Epidemiology and Psychiatric Sciences*, *19*(4), 326–332.

[18] **Noblet, A. and LaMontagne, A.D.** (2006). The role of workplace health promotion in addressing job stress, *Health promotion international*, *21*(4), 346–353.

[19] **Bzdok, D. and Meyer-Lindenberg, A.** (2018). Machine learning for precision psychiatry: opportunities and challenges, *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, *3*(3), 223–230.

[20] **D'Alfonso, S.** (2020). AI in mental health, *Current Opinion in Psychology*, *36*, 112–117.

[21] **Forooraghi, M.**, **Miedema, E.**, **Ryd, N. and Wallbaum, H.** (2020). Scoping review of health in office design approaches, *Journal of Corporate Real Estate*.

[22] **Organization, W.H.** *et al.* (2004). *Promoting mental health: Concepts, emerging evidence, practice: Summary report*, World Health Organization.

[23] **Moncrieff, J. and Pomerleau, J.** (2000). Trends in sickness benefits in Great Britain and the contribution of mental disorders, *Journal of Public Health*, *22*(1), 59–67.

[24] **Cattrell, A.**, **Harris, E.C.**, **Palmer, K.T.**, **Kim, M.**, **Aylward, M. and Coggon, D.** (2011). Regional trends in awards of incapacity benefit by cause, *Occupational medicine*, *61*(3), 148–151.

[25] **Murray, C.J.**, **Vos, T.**, **Lozano, R.**, **Naghavi, M.**, **Flaxman, A.D.**, **Michaud, C.**, **Ezzati, M.**, **Shibuya, K.**, **Salomon, J.A.**, **Abdalla, S.** *et al.* (2012). Disability-adjusted life years (DALYs) for 291 diseases and injuries in 21 regions, 1990–2010: a systematic analysis for the Global Burden of Disease Study 2010, *The lancet*, *380*(9859), 2197–2223.

[26] **Chopra, P.** (2009). Mental health and the workplace: issues for developing countries, *International Journal of Mental Health Systems*, *3*(1), 1–9.

[27] **Luciano, A. and Meara, E.** (2014). Employment status of people with mental illness: national survey data from 2009 and 2010, *Psychiatric Services*, *65*(10), 1201–1209.

[28] **Hanc, M.**, **McAndrew, C. and Ucci, M.** (2019). Conceptual approaches to wellbeing in buildings: A scoping review, *Building Research & Information*, *47*(6), 767–783.

[29] **Bergefurt, L.**, **Weijs-Perrée, M.**, **Appel-Meulenbroek, R. and Arentze, T.** (2022). The physical office workplace as a resource for mental health–A systematic scoping review, *Building and Environment*, *207*, 108505.

[30] **Danielsson, C.B.**, (2008). Office experiences, Product experience, Elsevier, pp.605–628.

[31] **Sander, E.L.J.**, **Caza, A. and Jordan, P.J.** (2019). Psychological perceptions matter: Developing the reactions to the physical work environment scale, *Building and Environment*, *148*, 338–347.

[32] **Roskams, M. and Haynes, B.** (2019). Salutogenic workplace design: A conceptual framework for supporting sense of coherence through environmental resources, *Journal of Corporate Real Estate*.

[33] **Murphey, D.**, **Barry, M. and Vaughn, B.** (2013). Mental Health Disorders. Adolescent Health Highlight. Publication# 2013-1., *Child Trends*.

[34] **Kessler, R.C.**, **van Loo, H.M.**, **Wardenaar, K.J.**, **Bossarte, R.M.**, **Brenner, L.**, **Ebert, D.**, **De Jonge, P.**, **Nierenberg, A.**, **Rosellini, A.**, **Sampson, N.** *et al.* (2017). Using patient self-reports to study heterogeneity of treatment effects in major depressive disorder, *Epidemiology and psychiatric sciences*, *26*(1), 22–36.

[35] **Ben Salem, Y.** (2022). A Brief Review of The Different Approaches for Mood Disorders Detection and Diagnosis, *2022 IEEE 9th International Conference on Sciences of Electronics, Technologies of Information and Telecommunications (SETIT)*, pp.529–536.

[36] **Dibeklioğlu, H., Hammal, Z., Yang, Y. and Cohn, J.F.** (2015). Multimodal detection of depression in clinical interviews, *Proceedings of the 2015 ACM on international conference on multimodal interaction*, pp.307–310.

[37] **Kessler, R.C., Chiu, W.T., Demler, O. and Walters, E.E.** (2005). Prevalence, severity, and comorbidity of 12-month DSM-IV disorders in the National Comorbidity Survey Replication, *Archives of general psychiatry*, *62*(6), 617–627.

[38] **Jablensky, A., McGrath, J., Herrman, H., Castle, D., Gureje, O., Evans, M., Carr, V., Morgan, V., Korten, A. and Harvey, C.** (2000). Psychotic disorders in urban areas: an overview of the Study on Low Prevalence Disorders, *Australian & New Zealand Journal of Psychiatry*, *34*(2), 221–236.

[39] **Ma, F.**, (2022). Diagnostic and Statistical Manual of Mental Disorders-5 (DSM-5), Encyclopedia of Gerontology and Population Aging, Springer, pp.1414–1425.

[40] **Siegel, J.A. and Sawyer, K.B.** (2019). Eating disorders in the workplace: A qualitative investigation of women's experiences, *Psychology of Women Quarterly*, *43*(1), 37–58.

[41] **Harrison, A., Mountford, V.A. and Tchanturia, K.** (2014). Social anhedonia and work and social functioning in the acute and recovered phases of eating disorders, *Psychiatry Research*, *218*(1-2), 187–194.

[42] **Sy, R., Ponton, K., De Marco, P., Pi, S. and IsHak, W.W.** (2013). Quality of life in anorexia nervosa: a review of the literature, *Eating disorders*, *21*(3), 206–222.

[43] **Thomas, E., Diale, B.M. and Victor-Aigbodion, V.** (2022). Workplace Experiences Of Youth Diagnosed With Attention Deficit Hyperactivity Disorder (Adhd), *Journal of Positive School Psychology*, 1306–1317.

[44] **Amaravathi, T., Murugan, M., Geetha, P.** *et al.* (2020). Combating attention deficit hyperactivity disorder with natural treatment.

[45] **Harris, J.L.** (2020). *The experience of adults with attention-deficit/hyperactivity disorder in the workplace*, Walden University.

[46] **Adamou, M., Arif, M., Asherson, P., Aw, T.C., Bolea, B., Coghill, D., Guðjónsson, G., Halmøy, A., Hodgkins, P., Müller, U.** *et al.* (2013). Occupational issues of adults with ADHD, *BMC psychiatry*, *13*(1), 1–7.

[47] **Stone, M.H.** (1993). Long-term outcome in personality disorders, *The British Journal of Psychiatry*, *162*(3), 299–313.

[48] **Skodol, A.E., Bender, D.S., Morey, L.C., Clark, L.A., Oldham, J.M., Alarcon, R.D., Krueger, R.F., Verheul, R., Bell, C.C. and Siever, L.J.** (2011). Personality disorder types proposed for DSM-5, *Journal of personality disorders*, *25*(2), 136.

[49] **Goodwin, G.M.** (2022). The overlap between anxiety, depression, and obsessive-compulsive disorder, *Dialogues in clinical neuroscience*.

[50] **Fineberg, N.A.**, **Chamberlain, S.R.**, **Goudriaan, A.E.**, **Stein, D.J.**, **Vanderschuren, L.J.**, **Gillan, C.M.**, **Shekar, S.**, **Gorwood, P.A.**, **Voon, V.**, **Morein-Zamir, S.** *et al.* (2014). New developments in human neurocognition: clinical, genetic, and brain imaging correlates of impulsivity and compulsivity, *CNS spectrums*, *19*(1), 69–89.

[51] **Bertl, M.**, **Metsallik, J. and Ross, P.** (2022). A systematic literature review of AI-based digital decision support systems for post-traumatic stress disorder, *Frontiers in Psychiatry*, *13*.

[52] **Meltzer, E.C.**, **Averbuch, T.**, **Samet, J.H.**, **Saitz, R.**, **Jabbar, K.**, **Lloyd-Travaglini, C. and Liebschutz, J.M.** (2012). Discrepancy in diagnosis and treatment of post-traumatic stress disorder (PTSD): treatment for the wrong reason, *The journal of behavioral health services & research*, *39*(2), 190–201.

[53] **Wilson, J.P. and Raphael, B.** (2013). *International handbook of traumatic stress syndromes*, Springer Science & Business Media.

[54] **North, C.S.** (2015). The classification of hysteria and related disorders: historical and phenomenological considerations, *Behavioral sciences*, *5*(4), 496–517.

[55] **Van der Kolk, B.A. and Van der Hart, O.** (1989). Pierre Janet and the breakdown of adaptation in psychological trauma, *American Journal of Psychiatry*, *146*(12), 1530–1540.

[56] **Canan, F. and North, C.S.** (2019). Dissociation and disasters: A systematic review, *World journal of psychiatry*, *9*(6), 83.

[57] **Verdejo-García, A.**, **Lawrence, A.J. and Clark, L.** (2008). Impulsivity as a vulnerability marker for substance-use disorders: review of findings from high-risk research, problem gamblers and genetic association studies, *Neuroscience & Biobehavioral Reviews*, *32*(4), 777–810.

[58] **Malick, R.** (2018). Prevention of substance use disorders in the community and workplace, *Indian journal of psychiatry*, *60*(Suppl 4), S559.

[59] **Takeuchi, H.**, **Yahata, N.**, **Lisi, G.**, **Tsurumi, K.**, **Yoshihara, Y.**, **Kawada, R.**, **Murao, T.**, **Mizuta, H.**, **Yokomoto, T.**, **Miyagi, T.** *et al.* (2022). Development of a classifier for gambling disorder based on functional connections between brain regions, *Psychiatry and Clinical Neurosciences*.

[60] **Edition, F.** *et al.* (2013). Diagnostic and statistical manual of mental disorders, *Am Psychiatric Assoc*, *21*(21), 591–643.

[61] **Follmer, K.B. and Jones, K.S.** (2018). Mental illness in the workplace: An interdisciplinary review and organizational research agenda, *Journal of Management*, *44*(1), 325–351.

[62] **Behle, H.** (2005). Moderators and mediators on the mental health of young participants in active labour market programmes: Evidence from East and West Germany, *International Review of Psychiatry*, *17*(5), 337–345.

[63] **Bakker, A.B. and Demerouti, E.** (2007). The job demands-resources model: State of the art, *Journal of managerial psychology*.

[64] **Warr, P.** (1990). The measurement of well-being and other aspects of mental health, *Journal of occupational Psychology*, *63*(3), 193–210.

[65] **Danna, K. and Griffin, R.W.** (1999). Health and well-being in the workplace: A review and synthesis of the literature, *Journal of management*, *25*(3), 357–384.

[66] **Diener, E.**, **Oishi, S. and Lucas, R.E.** (2003). Personality, culture, and subjective well-being: Emotional and cognitive evaluations of life, *Annual review of psychology*, *54*(1), 403–425.

[67] **Erickson, R.J. and Wharton, A.S.** (1997). Inauthenticity and depression: Assessing the consequences of interactive service work, *Work and occupations*, *24*(2), 188–213.

[68] **Wagner, D.T.**, **Barnes, C.M. and Scott, B.A.** (2014). Driving it home: How workplace emotional labor harms employee home life, *Personnel Psychology*, *67*(2), 487–516.

[69] **Wang, P.S.**, **Simon, G. and Kessler, R.C.** (2003). The economic burden of depression and the cost-effectiveness of treatment, *International journal of methods in psychiatric research*, *12*(1), 22–33.

[70] **Benach, J.**, **Muntaner, C. and Santana, V.** (2007). Employment conditions and health inequalities.

[71] **Sanderson, K. and Andrews, G.** (2006). Common mental disorders in the workforce: recent findings from descriptive and social epidemiology, *The Canadian Journal of Psychiatry*, *51*(2), 63–75.

[72] **Houtman, I.**, **Jettinghof, K. and Cedillo, L.** (2007). Raising awareness of stress at work in developing countires: a modern hazard in a traditional working environment: advice to employers and worker representatives.

[73] **Giri, S.**, **Farid, F.**, **Chowdhury, N. and Foster, J.** (2022). A Feasibility Study for Applying Explainable Predictive Models for the Detection of Mental Health Conditions.

[74] **Wilhelm, K.**, **Kovess, V.**, **Rios-Seidel, C. and Finch, A.** (2004). Work and mental health, *Social psychiatry and psychiatric epidemiology*, *39*(11), 866–873.

[75] **Mykletun, A. and Harvey, S.B.** (2012). Prevention of mental disorders: a new era for workplace mental health, *Occupational and Environmental Medicine*, *69*(12), 868–869.

[76] **Knudsen, A.K.**, **Øverland, S.**, **Aakvaag, H.F.**, **Harvey, S.B.**, **Hotopf, M. and Mykletun, A.** (2010). Common mental disorders and disability pension award: seven year follow-up of the HUSK study, *Journal of psychosomatic research*, *69*(1), 59–67.

[77] **Knudsen, A.K.**, **Harvey, S.B.**, **Mykletun, A. and Øverland, S.** (2013). Common mental disorders and long-term sickness absence in a general working population. The Hordaland Health Study, *Acta Psychiatrica Scandinavica*, *127*(4), 287–297.

[78] **Duan, Q.**, **Wang, G.**, **Wang, R.**, **Fu, C.**, **Li, X.**, **Wang, N.**, **Huang, Y.**, **Huang, X.**, **Song, T.**, **Zhao, L.** *et al.* (2020). SenseCare: A research platform for medical image informatics and interactive 3D visualization, *arXiv preprint arXiv:2004.07031*.

[79] **Hunt, D.L.**, **Haynes, R.B.**, **Hanna, S.E. and Smith, K.** (1998). Effects of computer-based clinical decision support systems on physician performance and patient outcomes: a systematic review, *Jama*, *280*(15), 1339–1346.

[80] **Jiang, F.**, **Jiang, Y.**, **Zhi, H.**, **Dong, Y.**, **Li, H.**, **Ma, S.**, **Wang, Y.**, **Dong, Q.**, **Shen, H. and Wang, Y.** (2017). Artificial intelligence in healthcare: past, present and future, *Stroke and vascular neurology*, *2*(4).

[81] **Beam, A.L. and Kohane, I.S.** (2016). Translating artificial intelligence into clinical care, *Jama*, *316*(22), 2368–2369.

[82] **Bishnoi, L. and Singh, S.N.** (2018). Artificial intelligence techniques used in medical sciences: a review, *2018 8th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*, IEEE, pp.1–8.

[83] **Miotto, R.**, **Wang, F.**, **Wang, S.**, **Jiang, X. and Dudley, J.T.** (2018). Deep learning for healthcare: review, opportunities and challenges, *Briefings in bioinformatics*, *19*(6), 1236–1246.

[84] **Topol, E.J.** (2019). High-performance medicine: the convergence of human and artificial intelligence, *Nature medicine*, *25*(1), 44–56.

[85] **Maniyar, A.A.**, **SH, J.K.**, **Nithej, N.**, **Ramya, H. and Aishwarya, T.** MACHINE LEARNING TECHNIQUES FOR STRESS PREDICTION IN WORKING EMPLOYEES SCIENCE & ENGINEERING.

[86] **Nassirtoussi, A.K.**, **Aghabozorgi, S.**, **Wah, T.Y. and Ngo, D.C.L.** (2014). Text mining for market prediction: A systematic review, *Expert Systems with Applications*, *41*(16), 7653–7670.

[87] **Yu, Q.**, **Miche, Y.**, **Séverin, E. and Lendasse, A.** (2014). Bankruptcy prediction using extreme learning machine and financial expertise, *Neurocomputing*, *128*, 296–302.

[88] **Jungherr, A.** (2016). Twitter use in election campaigns: A systematic literature review, *Journal of information technology & politics*, *13*(1), 72–91.

[89] **Wang, T.**, **Rudin, C.**, **Wagner, D. and Sevieri, R.** (2013). Learning to detect patterns of crime, *Joint European conference on machine learning and knowledge discovery in databases*, Springer, pp.515–530.

[90] **Kaur, H. and Wasan, S.K.** (2006). Empirical study on applications of data mining techniques in healthcare, *Journal of Computer science*, *2*(2), 194–200.

[91] **Herland, M.**, **Khoshgoftaar, T.M. and Wald, R.** (2014). A review of data mining using big data in health informatics, *Journal of Big data*, *1*(1), 1–35.

[92] **Shatte, A.B.**, **Hutchinson, D.M. and Teague, S.J.** (2019). Machine learning in mental health: a scoping review of methods and applications, *Psychological medicine*, *49*(9), 1426–1448.

[93] **Chen, M.**, **Hao, Y.**, **Hwang, K.**, **Wang, L. and Wang, L.** (2017). Disease prediction by machine learning over big data from healthcare communities, *Ieee Access*, *5*, 8869–8879.

[94] **Wiens, J. and Shenoy, E.S.** (2018). Machine learning for healthcare: on the verge of a major shift in healthcare epidemiology, *Clinical Infectious Diseases*, *66*(1), 149–153.

[95] **Jordan, M.I. and Mitchell, T.M.** (2015). Machine learning: Trends, perspectives, and prospects, *Science*, *349*(6245), 255–260.

[96] **Luo, J.**, **Wu, M.**, **Gopukumar, D. and Zhao, Y.** (2016). Big data application in biomedical research and health care: a literature review, *Biomedical informatics insights*, *8*, BII–S31559.

[97] **LeCun, Y.**, **Bengio, Y. and Hinton, G.** (2015). Deep learning, *nature*, *521*(7553), 436–444.

[98] **Mohr, D.C.**, **Zhang, M. and Schueller, S.M.** (2017). Personal sensing: understanding mental health using ubiquitous sensors and machine learning, *Annual review of clinical psychology*, *13*, 23.

[99] **Srividya, M.**, **Mohanavalli, S. and Bhalaji, N.** (2018). Behavioral modeling for mental health using machine learning algorithms, *Journal of medical systems*, *42*(5), 1–12.

[100] **Jeong, S. and Breazeal, C.L.** (2016). Improving smartphone users' affect and wellbeing with personalized positive psychology interventions, *Proceedings of the Fourth International Conference on Human Agent Interaction*, pp.131–137.

[101] **Garlapati, A.**, **Krishna, D.R.**, **Garlapati, K. and Narayanan, G.** (2020). Predicting Employees under Stress for Pre-emptive Remediation using Machine learning Algorithm, *2020 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT)*, IEEE, pp.315–319.

[102] **Ker, J.**, **Wang, L.**, **Rao, J. and Lim, T.** (2017). Deep learning applications in medical image analysis, *Ieee Access*, *6*, 9375–9389.

[103] **Vieira, S.**, **Pinaya, W.H. and Mechelli, A.** (2017). Using deep learning to investigate the neuroimaging correlates of psychiatric and neurological disorders: Methods and applications, *Neuroscience & Biobehavioral Reviews*, *74*, 58–75.

[104] **Durstewitz, D.**, **Koppe, G. and Meyer-Lindenberg, A.** (2019). Deep neural networks in psychiatry, *Molecular psychiatry*, *24*(11), 1583–1598.

[105] **Goodfellow, I.**, **Pouget-Abadie, J.**, **Mirza, M.**, **Xu, B.**, **Warde-Farley, D.**, **Ozair, S.**, **Courville, A. and Bengio, Y.** (2014). Generative adversarial nets Advances in neural information processing systems, *arXiv preprint arXiv:1406.2661*.

[106] **Singh, N.K. and Raza, K.** (2021). Medical image generation using generative adversarial networks: A review, *Health informatics: A computational perspective in healthcare*, 77–96.

[107] **Yi, X.**, **Walia, E. and Babyn, P.** (2019). Generative adversarial network in medical imaging: A review, *Medical image analysis*, *58*, 101552.

[108] **Kazeminia, S.**, **Baur, C.**, **Kuijper, A.**, **van Ginneken, B.**, **Navab, N.**, **Albarqouni, S. and Mukhopadhyay, A.** (2020). GANs for medical image analysis, *Artificial Intelligence in Medicine*, *109*, 101938.

[109] **Reed, S.**, **Akata, Z.**, **Yan, X.**, **Logeswaran, L.**, **Schiele, B. and Lee, H.** (2016). Generative adversarial text to image synthesis, *International conference on machine learning*, PMLR, pp.1060–1069.

[110] **Karras, T.**, **Aila, T.**, **Laine, S. and Lehtinen, J.** (2017). Progressive growing of gans for improved quality, stability, and variation, *arXiv preprint arXiv:1710.10196*.

[111] **Jin, Y.**, **Zhang, J.**, **Li, M.**, **Tian, Y.**, **Zhu, H. and Fang, Z.** (2017). Towards the automatic anime characters creation with generative adversarial networks, *arXiv preprint arXiv:1708.05509*.

[112] **Ledig, C.**, **Theis, L.**, **Huszár, F.**, **Caballero, J.**, **Cunningham, A.**, **Acosta, A.**, **Aitken, A.**, **Tejani, A.**, **Totz, J.**, **Wang, Z.** *et al.* (2017). Photo-realistic single image super-resolution using a generative adversarial network, *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp.4681–4690.

[113] **Wiatrak, M. and Albrecht, S.** (2019). Stabilizing generative adversarial network training: a survey. arXiv preprint arXiv: 191000927.

[114] **Pan, Z.**, **Yu, W.**, **Yi, X.**, **Khan, A.**, **Yuan, F. and Zheng, Y.** (2019). Recent progress on generative adversarial networks (GANs): A survey, *IEEE access*, *7*, 36322–36333.

[115] **Saxena, D. and Cao, J.** (2021). Generative adversarial networks (GANs) challenges, solutions, and future directions, *ACM Computing Surveys (CSUR)*, *54*(3), 1–42.

[116] **Gui, J.**, **Sun, Z.**, **Wen, Y.**, **Tao, D. and Ye, J.** (2021). A review on generative adversarial networks: Algorithms, theory, and applications, *IEEE transactions on knowledge and data engineering*.

[117] **Isola, P.**, **Zhu, J.Y.**, **Zhou, T. and Efros, A.A.** (2017). Image-to-image translation with conditional adversarial networks, *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp.1125–1134.

[118] **Mirza, M. and Osindero, S.** (2014). Conditional generative adversarial nets, *arXiv preprint arXiv:1411.1784*.

[119] **Liu, Z.**, **Bicer, T.**, **Kettimuthu, R.**, **Gursoy, D.**, **De Carlo, F. and Foster, I.** (2020). TomoGAN: low-dose synchrotron x-ray tomography with generative adversarial networks: discussion, *JOSA A*, *37*(3), 422–434.

[120] **Choi, H. and Lee, D.S.** (2018). Generation of structural MR images from amyloid PET: application to MR-less quantification, *Journal of Nuclear Medicine*, *59*(7), 1111–1117.

[121] **Ghorbani, A.**, **Natarajan, V.**, **Coz, D. and Liu, Y.** (2020). Dermgan: Synthetic generation of clinical skin images with pathology, *Machine Learning for Health Workshop*, PMLR, pp.155–170.

[122] **Yu, Z.**, **Xiang, Q.**, **Meng, J.**, **Kou, C.**, **Ren, Q. and Lu, Y.** (2019). Retinal image synthesis from multiple-landmarks input with generative adversarial networks, *Biomedical engineering online*, *18*(1), 1–15.

[123] *OSMI*, `https://osmihelp.org/research`, Retrieved October 5, 2022, from https://osmihelp.org/research.

[124] **Elmunsyah, H.**, **Mu'awanah, R.**, **Widiyaningtyas, T.**, **Zaeni, I.A. and Dwiyanto, F.A.** (2019). Classification of employee mental health disorder treatment with k-nearest neighbor algorithm, *2019 International Conference on Electrical, Electronics and Information Engineering (ICEEIE)*, volume 6, IEEE, pp.211–215.

[125] **Katarya, R. and Maan, S.** (2020). Predicting Mental health disorders using Machine Learning for employees in technical and non-technical companies, *2020 IEEE International Conference on Advances and Developments in Electrical and Electronics Engineering (ICADEE)*, IEEE, pp.1–5.

[126] **Mallick, S. and Panda, M.** Mental Health Illness Disease Prediction Using Most Common Feature in Tech Survey Dataset.

[127] **Reddy, U.S.**, **Thota, A.V. and Dharun, A.** (2018). Machine learning techniques for stress prediction in working employees, *2018 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)*, IEEE, pp.1–4.

[128] **Laijawala, V.**, **Aachaliya, A.**, **Jatta, H. and Pinjarkar, V.** (2020). Classification algorithms based mental health prediction using data mining, *2020 5th International Conference on Communication and Electronics Systems (ICCES)*, IEEE, pp.1174–1178.

[129] **Ogunseye, E.O.**, **Adenusi, C.A.**, **Nwanakwaugwu, A.C.**, **Ajagbe, S.A. and Akinola, S.O.** (2022). Predictive analysis of mental health conditions using AdaBoost algorithm, *ParadigmPlus*, *3*(2), 11–26.

[130] **Saranya, S. and Kavitha, N.** (2022). ROBUST FEATURE SELECTION WITH CHICKEN SWARM INTELLIGENCE IMPROVED MULTILAYER PERCEPTRON FOR EARLY DETECTION OF MENTAL ILLNESS DISORDER, *Journal of Theoretical and Applied Information Technology*, *100*(10).

[131] **Fayyad, U.**, **Piatetsky-Shapiro, G. and Smyth, P.** (1996). From data mining to knowledge discovery in databases, *AI magazine*, *17*(3), 37–37.

[132] **Friedman, J.H.** (1998). Data Mining and Statistics: What's the connection?, *Computing science and statistics*, *29*(1), 3–9.

[133] **Maimon, O. and Rokach, L.** (2005). Data mining and knowledge discovery handbook.

[134] **Luckert, M. and Schaefer-Kehnert, M.** (2016). *Using machine learning methods for evaluating the quality of technical documents*.

[135] **Goodfellow, I.**, **Pouget-Abadie, J.**, **Mirza, M.**, **Xu, B.**, **Warde-Farley, D.**, **Ozair, S.**, **Courville, A. and Bengio, Y.** (2020). Generative adversarial networks, *Communications of the ACM*, *63*(11), 139–144.

[136] **Kahng, M.**, **Thorat, N.**, **Chau, D.H.**, **Viégas, F.B. and Wattenberg, M.** (2018). Gan lab: Understanding complex deep generative models using interactive visual experimentation, *IEEE transactions on visualization and computer graphics*, *25*(1), 310–320.

[137] **Tang, H.**, **Xu, D.**, **Liu, H. and Sebe, N.** (2019). Asymmetric generative adversarial networks for image-to-image translation, *arXiv preprint arXiv:1912.06931*.

[138] **Zhang, H.**, **Xu, T.**, **Li, H.**, **Zhang, S.**, **Wang, X.**, **Huang, X. and Metaxas, D.N.** (2017). Stackgan: Text to photo-realistic image synthesis with stacked generative adversarial networks, *Proceedings of the IEEE international conference on computer vision*, pp.5907–5915.

[139] **Regmi, K. and Borji, A.** (2018). Cross-view image synthesis using conditional gans, *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, pp.3501–3510.

[140] **Lin, C.H.**, **Yumer, E.**, **Wang, O.**, **Shechtman, E. and Lucey, S.** (2018). St-gan: Spatial transformer generative adversarial networks for image compositing, *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp.9455–9464.

[141] **Mo, S.**, **Cho, M. and Shin, J.** (2018). Instagan: Instance-aware image-to-image translation, *arXiv preprint arXiv:1812.10889*.

[142] **Alotaibi, A.** (2020). Deep generative adversarial networks for image-to-image translation: A review, *Symmetry*, *12*(10), 1705.

[143] **Ronneberger, O.**, **Fischer, P. and Brox, T.** (2015). U-net: Convolutional networks for biomedical image segmentation, *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18*, Springer, pp.234–241.

[144] **Li, C. and Wand, M.** (2016). Precomputed real-time texture synthesis with markovian generative adversarial networks, *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part III 14*, Springer, pp.702–716.

[145] **Isola, P.** (2017). *Image-to-image translation with conditional adversarial nets*, `https://github.com/phillipi/pix2pix.git`.

[146] **Srivastava, N.**, **Hinton, G.**, **Krizhevsky, A.**, **Sutskever, I. and Salakhutdinov, R.** (2014). Dropout: a simple way to prevent neural networks from overfitting, *The journal of machine learning research*, *15*(1), 1929–1958.

[147] **Brownlee, J.** (2019). A gentle introduction to pix2pix generative ad-versarial network, *(Last checked on*.

[148] **Marathe, A.**, **Takalikar, M.S. and Bhowmick, T.** (2022). Applied Single Image Super-Resolution for Aerial Imagery Enhancement, *2022 IEEE Global Conference on Computing, Power and Communication Technologies (GlobConPT)*, IEEE, pp.1–7.

[149] **Hoque, M.R.U.**, **Burks, R.**, **Kwan, C. and Li, J.** (2019). Deep learning for remote sensing image super-resolution, *2019 IEEE 10th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)*, IEEE, pp.0286–0292.

[150] **Hawkins, D.M.** (2004). The problem of overfitting, *Journal of chemical information and computer sciences*, *44*(1), 1–12.

[151] **Theis, L.**, **Oord, A.v.d. and Bethge, M.** (2015). A note on the evaluation of generative models, *arXiv preprint arXiv:1511.01844*.

[152] **Kingma, D.P. and Welling, M.** (2013). Auto-encoding variational bayes, *arXiv preprint arXiv:1312.6114*.

[153] **Patel, P.** (2018). *Perceived Workplace Factors and their Influence on Self-Reported Mental Health Service Seeking Among Technology Workers*.

[154] **Aggreh, M.**, **Akinsiku, T.**, **Ewuzie, A.**, **Hessings, F.**, **Jones, W.**, **McLaverty, D.**, **Mugoma, W.E.**, **Obed, V. and Oduala, E.** Mental Health in the Tech Workplace: What are the strongest.

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OTHER PUBLICATIONS, PRESENTATIONS AND PATENTS:

- **Farid F.**, Moghaddasi S.H., , Pakinasab N.,Moghaddasi S.O.(2014). Offering a model to measure the impact of the servqual model of service quality on brand loyalty with emphasis on the role of brand switching cost, *Indian Journal of Fundamental and Applied Life Sciences,* 2231– 6345.

- Donyatalab Y., Kutlu Gündoğdu F., **Farid F.** , Shishavan A., Farrokhizadeh E., Kahraman C. (2021). Distance and Similarity Measures Under Spherical Fuzzy Environment and Their Application to Pattern Recognition. *Journal of Multiple-Valued Logic and Soft Computing,* 37(3-4):363-407.

- **Farid F.**, Donyatalab Y. (2021). Novel spherical fuzzy eco-holonic concept in sustainable supply chain of aviation fuel, *Intelligent and Fuzzy Techniques in Aviation 4.0: Theory and Applications,* 201-235.

- Donyatalab Y., **Farid F.** (2021). Spherical fuzzy linear assignment with objective weighting concept in the sustainable supply chain of aviation fuel. *Intelligent and Fuzzy Techniques for Emerging Conditions and Digital Transformation: Proceedings of the INFUS 2021 Conference, held August 24-26, 2021. Volume 2,* 766-776, Istanbul, Turkey.

- Donyatalab Y., **Farid F.** (2021). Spherical fuzzy inference systems (S-FIS) to control UAVs' communication technologies. *Intelligent and Fuzzy Techniques in Aviation 4.0: Theory and Applications,* 459-496.

- Donyatalab Y., Kutlu Gündoğdu F., **Farid F.** , Shishavan A., Farrokhizadeh E., Kahraman C. (2022). Novel spherical fuzzy distance and similarity measures and their applications to medical diagnosis. *Expert Systems with Applications,* 0957-4174.

- **Farid F.**, Donyatalab Y. (2022). Optimal selecting of sanitarium sites for COVID-19 patients in Iran by applying an integrated ELECTRE-VIKOR method in q-ROFSs environment, *Intelligent and Fuzzy Techniques for Emerging Conditions and Digital Transformation: Proceedings of the INFUS 2021 Conference, held August 24-26, 2021,*Istanbul, Turkey.

- **Farid F.**, Donyatalab Y. (2022). Sustainable Supply Chain of Aviation Fuel Based on Analytical Hierarchy Process (AHP) Under Uncertainty of q-ROFSs,*Intelligent and Fuzzy Techniques for Emerging Conditions and Digital Transformation: Proceedings of the INFUS 2021 Conference, held August 24-26, 2021. Volume 2,* 578-588.

- **Farid F.**, Donyatalab Y. (2022). An Intelligent Understanding of the Post-COVID-19 Uncertainty: Provided Guidelines and Strategies for Resilient Supply Chain Networks,*Intelligent and Fuzzy Systems: Digital Acceleration and The New Normal-Proceedings of the INFUS 2022 Conference,held July 19-21, 2022*, Istanbul, Turkey.

- Donyatalab Y., **Farid F.** (2022). Kidney Transplantation and Allocation Decision Support Analysis Under COVID-19 Uncertainty,*Intelligent and Fuzzy Systems: Digital Acceleration and The New Normal-Proceedings of the INFUS 2022 Conference, Volume 2*, 250-262, Istanbul, Turkey.