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A SURVEY ON MACHINE AND DEEP LEARNING TECHNIQUES USED FOR MENTAL HEALTH DIAGNOSIS AND RISK ESTIMATE

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Abstract: Mental health is now starting to use machine learning models to diagnose psychological disorders and make prognostications on the risk factors. These models review intricate clinical, behavioral, and social patterns in data as a means of enhancing early identification, individualized attention, and strategies to cognize risk annotations to mental health. This paper discusses the use of ML in healthcare, particularly as it relates to the area of mental health risk assessment and diagnosis. Clinical and community health management are the contexts in which these ML methods are explained, and they are categorized as supervised, unsupervised, and reinforcement learning. Reviews are carried out of the popular models such as K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Convolutional Neural Network (CNN), Logistic Regression (LR), and Extreme Learning Machine (ELM) on their use in mental health. The paper sheds light on ML-based risk prediction models that use demographic, genetic, and clinical data to highlight high-risk patients so that they can be addressed in advance and help insert personalized care. Also, it looks in the area of severity prediction models of mental health conditions, including depression, via standardized scales, such as PHQ-9 and BDI. The idea of symptom profiling is presented to treat heterogeneity regarding depressive symptoms and advance individualized care. This article identifies the prospects of ML in developing precision mental healthcare.

Keywords: Mental Health Diagnosis, Machine Learning, Risk Prediction, Mental Health Disorders, Predictive Analytics.

1 INTRODUCTION

Medical model of mental health historically 'explains' uncomfortableness as indicators of 'mental illnesses. Nevertheless, functional psychiatric diagnoses are worrying because of no objective biomarkers to create these classifications [1]. Changes in diagnostic schemes, including the Diagnostic and Statistical Manual of Mental Disorders (DSM) and International Statistical Classification of Diseases and Related Health Problems (ICD) are frequently made on a basis of expert opinion and personal judgments on what is considered to be a healthy or unhealthy mind. Thus, doubts about the utility and reliability of diagnostic labels have been voiced [2]. Research demonstrates the unpopularity of the diagnostic criteria among the professionals and a poor amount of evidence that contributes to the diagnosis in enhancing the outcomes of treatment procedures or to explain the distress of an individual.

To address these limitations, ML and DL techniques are increasingly applied in mental health for early diagnosis, risk prediction, and intervention planning. By analyzing complex, high-dimensional datasets, ML models can uncover latent patterns associated with various mental health conditions, offering data-driven insights.

Models for risk prediction have been tested in a variety of demographics. To illustrate the point, pertinent risk factors were used to build a model that might predict mental health issues in Chinese soldiers [3][4]. Similarly, among college students, the variability and complexity of mental health issues present challenges in building robust models [5]. Nonetheless, such models are critical for early screening, prevention, and reduction of mental health morbidity

Attention on ML-based predictive analytics has increased in response to the growing number of student mental health illnesses [6]. Because mental health has such a profound impact on emotional stability, social functioning, and behavioral health, there is a growing need for innovative, tech-driven approaches to early detection and treatment of mental health problems. Machine learning (ML) provides a methodical way to examine mental health records, social media data, and brain imaging scans for signs of distress [7]. ML techniques, including supervised and unsupervised learning. Clinicians can use these trained models to aid in diagnosis and risk assessment for mental health issues, which in turn can inform individualized treatment plans and clinical decision-making [8]. For mental health, ML allows for early and precise prediction, which helps to overcome the limits of traditional diagnosis approaches.

1.1 Structure of the Paper

The structured of the paper is as follows: Section 2 covers the fundamentals of mental health disorders. Section 3 highlights the role of ML in mental healthcare. Sections 4 and 5 discuss diagnostic and risk prediction models. Section 6 presents a literature review. Section 7 concludes with key findings and future research directions.

2 FUNDAMENTALS OF MENTAL HEALTH DISORDERS

Depression, anxiety, bipolar disorder, schizophrenia, and dementia are notable examples of mental health problems, which include a variety of illnesses that substantially impact mood, thinking, and behaviour. Mood swings in bipolar disorder, memory loss in dementia, persistent sadness or hopelessness in depression, and delusions and hallucinations in schizophrenia are just a few of the unique symptoms that can greatly affect a person's ability to function and quality of life. Everyone from people to their families to healthcare institutions to society as a whole bear the brunt of these illnesses [9]. Improving patient outcomes, fostering recovery, and supporting successful society reintegration requires early diagnosis, timely and effective treatment, and persistent psychosocial support.

2.1 Common Mental Health Disorders

Mental health issues such as depression, anxiety, bipolar disorder, schizophrenia, and dementia impact millions of people around the world. They impair emotional, cognitive, and social functioning, often leading to disability, reduced quality of life, and increased mortality. Early diagnosis, effective treatment, and ongoing support are crucial for enhancing patient outcomes and facilitating societal reintegration are as follows:

2.1.1 Depression

One of the leading causes of disability, depression is on par with anxiety as the most frequent mental condition. 28 Depression is characterized by a lack of joy and interest in past activities. 34 Suicide is a major concern when social functioning is impaired, which might have an effect on schooling or employment.

2.1.2 Anxiety

Anxiety begins when the body's "fight-or-flight" response is overactive in response to a real or perceived threat, or when the danger is misjudged. Symptoms manifested by these illogical fears include a plethora of physical manifestations, including but not limited to: a racing heart rate, difficulty breathing, chest discomfort, syncope, high levels of bewilderment and impaired memory. Anxious people usually stay away from things that make them anxious.

2.1.3 Bipolar disorder

The global prevalence of bipolar disorder is close to 46 million. Mood swings between normal and manic-depressive episodes are typical [10]. Narcissism, accelerated speech, and inflated self-esteem are characteristic symptoms of mania. Death and disability rates are higher, and people with bipolar disorder have a lower quality of life overall.

2.1.4 Schizophrenia and Other Psychoses

Visual and auditory hallucinations accompany the classic psychotic symptoms of schizophrenia, which include altered perception, mood, and behaviour. People with schizophrenia cannot function or participate normally in society unless they receive treatment. However, with the right support system in place, people with schizophrenia can reintegrate into society and lead healthy, productive lives.

2.1.5 Dementia

A diagnosis of mild cognitive impairment is made when there is an objective decrease in cognitive abilities when compared to a previous time point, but the patient is still able to manage their daily activities independently and with little assistance. In order to confirm a diagnosis of dementia, more evidence of substantial problems with daily functioning that impact the individual's autonomy must be shown.

2.2 Risk Factors and Indicators

The four levels of the work system that are responsible for factors related to anxiety and depression are external, individual, work/unit, and organizational (Figure 1).

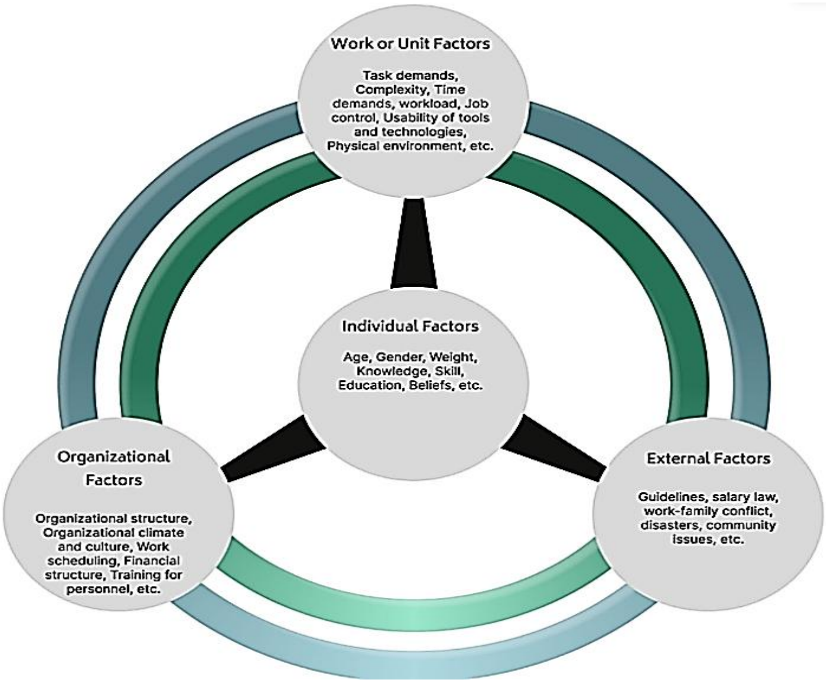

Figure 1: Understanding the causes of mental health issues at the organizational level

The main risk factors related to depression and anxiety are as follows:

2.2.1 Individual Factors

Personal risk factors included things like age, gender, marital status, occupation, health, quality of sleep, professional demeanour, degree of education, number of children, resilience, belief in one's own abilities, and smoking. There are a number of studies that list being a woman as a risk factor. Some studies also looked at age as a risk factor; for example, one found that people between the ages of 29 and 36 had the greatest prevalence of anxiety [11]. Conversely, fear of abandonment and other mental health issues are associated with married women. Another known association factor is parenthood or having children. As far as mental health is concerned, risk factors include things like a poor health status (physical or mental), a history of mental disorders, a chronic illness, and a history of poor physical health.

2.2.2 Work and Unit Factors

Employees face risks on the workplace and in the unit as a whole due to variables such as frequent patient contact, high-risk work situations (frontline), specific job duties (nursing), lack of management oversight, juggling multiple departments, inadequate PPE, and heavy workloads. Most studies believe the work title and kind to be a crucial element, particularly in the nursing profession. A meta-analysis found that the incidence of mental health issues across different types of healthcare workers, such as students, allied health professionals, support staff, and doctors, vary significantly [12]. Also included here are specific occupations and titles at the intermediate and upper levels of the professional hierarchy.

2.2.3 External Factors

The presence or absence of social support was cited as a major risk factor, while its receipt was cited as a protective factor. Factors such as social stigma, fear of infecting loved ones, and geographical location (continents), At this stage, social seclusion and quarantine were major considerations.

2.2.4 Organizational Factors

Several significant risk factors are present at this level, including alterations to the organizational structure and atmosphere, modifications to work schedules, insufficient training, and a lack of personal protective equipment. This specific level has been the focus of study with the following risk factors: support from the employer, team cohesion, insufficient backing from hospital administration, and unclear job expectations.

2.3 Challenges in Mental Health Diagnosis

Here are the challenges in mental health diagnosis presented in below:

- **Lack of Objective Biomarkers:** Subjective clinical evaluations and patient self-reports are crucial in the diagnosis of mental health illnesses because there are frequently no biochemical or physiological signs.
- **Symptom Overlap and Comorbidity:** Many mental disorders share similar symptoms (e.g., anxiety and depression), leading to diagnostic ambiguity and difficulty distinguishing between co-occurring conditions.

- **Diagnostic Heterogeneity:** Individuals diagnosed with the same condition may present with varying symptom profiles and severities, complicating standardization of diagnosis.
- **Cultural and Linguistic Bias:** Diagnostic tools and criteria can lack cultural specificity which translates to misdiagnosis or under diagnosis of diverse populations.
- **Temporal Instability of Symptoms:** Symptoms of mental health can be dynamic and episodic in nature where the classic assessment tends to be non-dynamic and can fail to capture changes over time.
- **Stigma and Access Barriers:** Social stigma, discrimination fear, and deficit in mental health resources make people unable to receive timely diagnosis and treatment.

There is a deficiency of objective biomarkers, symptom congruence, cultural bias, and symptom variability, which hinder mental health diagnosis. These issues, coupled with stigma and care inaccessibility illustrate the necessity of more robust and data-driven diagnostic methods that are also all-inclusive.

3 MACHINE LEARNING FOR MENTAL HEALTH IN HEALTHCARE

Predictive analytics, early health diagnosis, personalized treatment, and clinical assistance decision-making are some of the ways in which ML is transforming mental health in healthcare systems. In it, the three main branches of ML supervised, unsupervised, and reinforcement learning are categorized, and their applications in healthcare and population health management are detailed. Basically, these methods use large-scale health data to improve the rate and fidelity in delivering mental health care through bi-directional data-driven intervention and smarter, more timely choices and decisions.

3.1 Machine Learning in Healthcare

ML is an AI technique that teaches algorithms to make predictions or take actions without human intervention through the use of data. Disease diagnosis, treatment, and prevention stand to benefit greatly from ML application in healthcare. The ML-based remote patient monitoring system, shown in Figure 2, enables healthcare providers to continuously and instantly monitor patients by collecting data measured on their bodies through smart devices, sending it to the cloud, and then analyzing it using ML techniques.

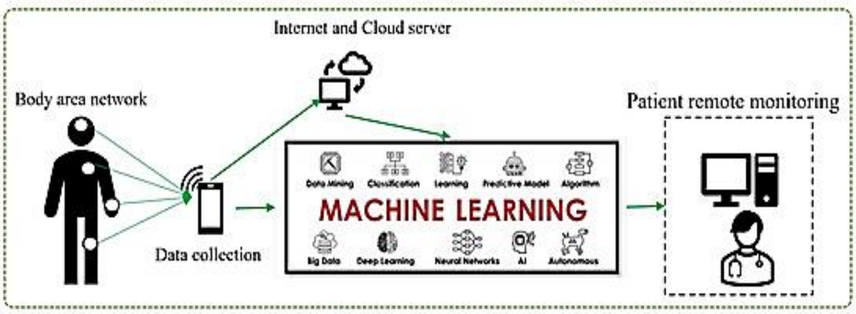

Figure 2: Machine learning as it pertains to healthcare

ML has several possible uses in the medical field, including:

- **Predictive Analytics:** ML algorithms may sift through claims data and electronic health records, among other sources, to forecast medical outcomes including hospital readmissions and the beginning of chronic diseases [13]. Doctors and nurses will be able to keep a closer eye on their patients and avoid individuals with a higher risk of adverse effects because of this.
- **Diagnosis and Treatment:** Medical imaging data, including X-rays and CT scans, can be used to train ML algorithms that will ultimately decide the best treatment plan for a patient.
- **Personalized Medicine:** ML can be used to find out, based on a patient's unique traits such their genetic composition and health background, which treatments have the best chance of working.
- **Clinical Decision Support:** Healthcare practitioners can make better decisions about patient care with the help of clinical decision support systems that are augmented with ML algorithms.
- **Population Health Management:** To develop public health initiatives, ML can be employed to take an analysis of data concerning numerous people to draw out trends and patterns that may be informative in the development of such initiatives.

ML has the ability to revolutionize healthcare by enhancing patient outcomes, reducing costs, and making the system more efficient.

3.2 Popular Machine Learning Techniques in Healthcare

ML is a subfield of AI that posits computers may learn to do certain tasks automatically, without the need for human intervention or explicit coding. Building algorithms and models that generalize things in the data is the basic goal of ML. These systems should be able to make good predictions or decisions based on new data based on what the data may reveal about patterns. The three main categories of ML methods are reinforcement learning, unsupervised learning, and supervised learning (Figure 3).

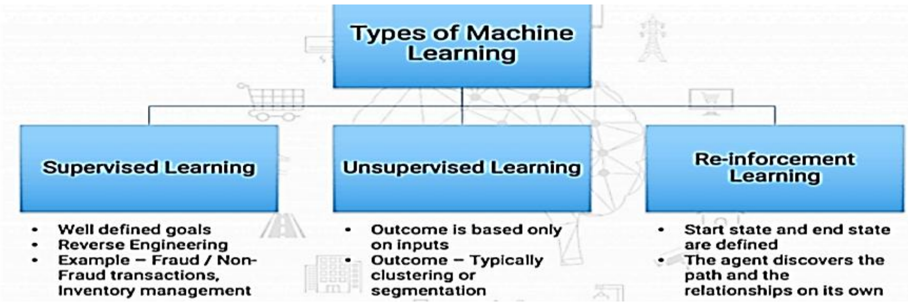

Figure 3: Types of Machine learning

ML techniques in healthcare system are as follows:

3.2.1 Supervised Learning

In supervised learning, a model is taught to associate input data with matching labels by means of labelled data during training [14]. In classification and regression, for example, this type of learning is used to train a model to predict a continuous or categorical value from a set of input features.

3.2.2 Unsupervised Learning

Training models using unlabeled data to uncover patterns, correlations, or structures within the data is what unsupervised learning is all about. The unsupervised learning techniques of dimensionality reduction and clustering, for example, help find data clusters and reduce data dimensionality while preserving important information.

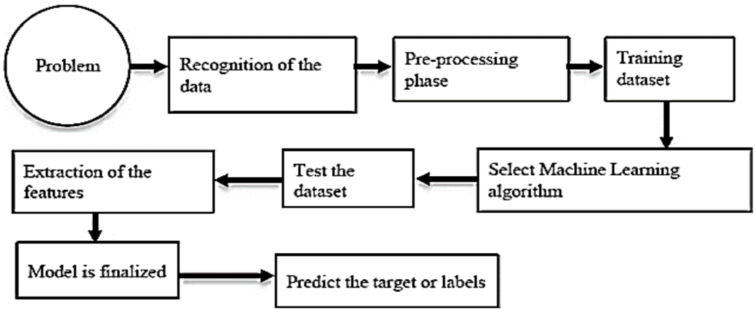

Figure 4: Workflow of unsupervised learning

Unsupervised learning is widely used in the processing of multimedia content (as shown in Figure 4) [15], as clustering and partitioning of data in the absence of class labels is often a requirement.

3.2.3 Reinforcement Learning Algorithm

In reinforcement learning, an agent learns from its interactions with its environment, which can be either positive or negative, and then uses this information to improve its future interactions in order to maximize its cumulative reward. Gambling and autonomous navigation are two examples of activities that frequently use this form of learning since they both need decision-making and sequential actions.

4 MACHINE LEARNING MODELS FOR MENTAL HEALTH DIAGNOSIS

Mental health diagnosis has seen extensive use of a variety of ML and DL models, including KNN, SVM, CNN, LSTM, GRU, and XLNet. These models are particularly effective in stress detection and mental health assessment through the analysis of physiological signals, textual data, and sequential patterns, enabling more accurate and automated identification of psychological conditions.

4.1 Machine Learning Models

ML uses mathematical modelling as a framework to categorize, forecast trends, and identify outliers in given time series. Several research have shown that ML can be used to classify diseases and extract features from medical records:

4.1.1 K-Nearest Neighbour (KNN):

Evidence suggests that KNN can successfully classify emotions based on EEG data. First proposed in 1951, it is a technique for guided learning. It's not uncommon to see KNN employed for regression and classification. Many people think that KNN is the simplest ML model out there. Thus, the idea that "the majority carries the day" is advanced. In a plurality vote, neighbors' votes determine an object's classification. The sensitivity of KNN algorithms to the real data structure is noteworthy.

4.1.2 Support Vector Machine (SVM):

One supervised ML methodology that has seen widespread use for regression problems is SVM, a kernel-based learning method. Its classification of PSG datasets has been the subject of extensive research and use [16]. Results from numerous research have shown that SVM outperforms its unsupervised counterparts in terms of accuracy. Its efficiency in classification and regression data analysis is comparable to that of KNN.

4.1.3 Logistic Regression (LR):

LR uses a logistic function on the dependent variable to model the relationship between a restricted set of features and the relevant treatment results. This is done using processed and feature-extracted datasets. The coefficients of the LR model have been identified as markers for feature interpretation.

4.1.4 Convolutional Neural Network (CNN):

Two primary kinds of CNN layers are the convolutional layer and the max-pooling layer. Common applications of convolutional neural networks (CNNs) include image identification and feature extraction. Due to the limitations of CNNs on its own, a CNN-LSTM hybrid model has been thoroughly studied on PSG datasets for time-series data forecasting. Because of its chaotic and random characteristics, it offered a non-linear domain for EEG-based analysis and produced very accurate results.

4.1.5 Multi-Layer Perceptron (MLP):

MLP is an example of a feedforward ANN with input, output, and hidden layers. It is recognised as the method that establishes the foundation of an intricate neural network. Non-linearly separable data can be categorized using MLP. Regression and classification tasks on challenging or complicated datasets can be solved using MLP's resilient architecture.

4.2 Deep Learning Models

LSTM, GRU, and XLNet are advanced DL models widely used in mental health diagnosis, particularly for stress detection through the analysis of sequential and textual data. LSTM and GRU are capable of modeling temporal and sequential patterns of physiological data and language, so that they can detect the correct mental health conditions. XLNet also has another advantage of diagnostic performance since it takes advantage of bidirectional contextual knowledge which fits it to analyze the user-generated information like social media posts and online forums. Herein below is this DL model:

4.2.1 Long Short-Term Memory (LSTM):

The LSTM neural network architecture shows a lot of promise for stress scan systems. Because of their exceptional ability to recognize and understand complex temporality-based relationships in sequential data, LSTMs are a great fit for stress analysis and the analysis of any temporal pattern in sequential data, including physiological signals and behavioral factors [17]. The ability of the LSTM to efficiently detect tiny stress signals is enhanced by its selective revision capability in extended sequences [18]. By utilizing LSTM networks, stress scan systems could surpass the existing state of the art in error-free and dependable stress detection algorithms when it comes to modelling and comprehending the dynamism of stress responses.

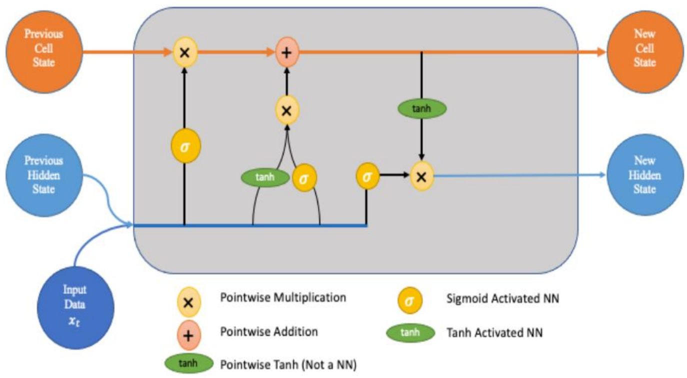

Figure 5: Structure of LSTM

Figure 5 presents the structure of an LSTM cell, displaying features of input, previous states, and gates interacting using pointwise operations and activations in an update of the cell state and hidden state and perform the learning of sequences of dependence in sequence data.

4.2.2 The Gated Recurrent Unit (GRU):

For stress detection using natural language processing, the GRU is a crucial part of the stress scan system. GRU is an RNN design that often finds statistical sequential chains to be useful [19]. The goal of using GRU to a stress scan is to find linguistic indicators of stressful situations by analyzing and interpreting patterns in text inputs, written responses, or social media posts.

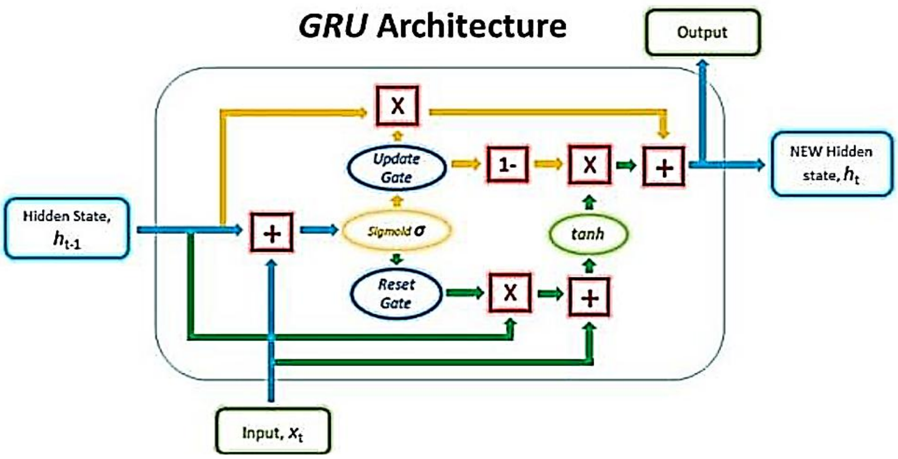

Figure 6: GRU Architecture

The GRU architecture is depicted in Figure 6, in which both the update and reset gates determine the information flow. It effectively updates the hidden state using the point-wise operations and activations (sigmoid and tanh), making it less complex and simpler when compared to LSTM since the dependencies of the sequential data are captured.

4.2.3 XL Net Algorithm:

Transformer-based language model XLNet can become a critical aspect of improving stress scan systems. By being the system capable of modeling the bidirectional contextual information and representing complex relations within the text information, XLNet can enable better and more refined processing of user-generated data (texts along with any related input regarding the user topics, including the stress-related ones). With the help of pre-training on a wide variety of data, XLNet is able to identify fine grained language features related to expression of stresses.

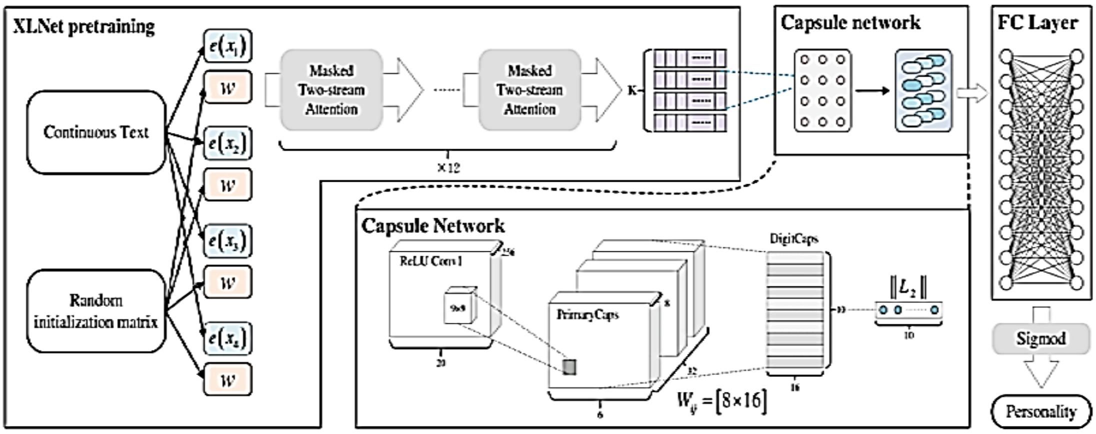

Figure 7: Structure of XLNet

Figure 7 shows an architecture which uses pretraining by an XLNet-based model combined with masked two-stream attention and then a Capsule Network to extract hierarchical features. The predictions are done using fully connected layers with a sigmoid activation in-between the layers to predict the personality of a given sentence or continuous text.

The model of ML and DL (KNN, SVM, LSTM, GRU and XLNet), can be used to improve the diagnosis of mental health: these models allow analyzing both physiological and textual data and implement stress identification successfully and automatically.

5 MACHINE LEARNING IN MENTAL HEALTH RISK PREDICTION

The section discusses about how ML models can be used to guess the chance of getting mental health problems and how bad those chances are, with a focus on customizing risk and controlling the variety of symptoms [20]. With tools like the Patient Health Questionnaire (PHQ-9) and the Beck Depression Inventory (BDI), the models help with correctly grading how bad the problem is and allow for quick, data-driven action. Individualized mental care planning can use ML because it helps find illnesses early and make plans for personalized treatment.

5.1 Risk Prediction Models

Data science-based risk prediction tools have been created to guess when mental disorders will happen. Such models get information about each person's risk from a variety of sources, including demographic, genetic, and clinical data. According to these models, they are very accurate, which means they can help the doctor focus on the people who are most likely to get sick and plan ways to keep that from happening. ML models can help figure out when a person will become depressed or nervous by looking at the stressful events in their childhood and their genetic predispositions. When it comes to tailoring treatments to each person based on their risk factors profile, risk prediction models are specially helpful. Patients who are at a high risk of developing disorders can be given preventative steps [21], such as direct treatment or changes to their lifestyle, which will stop those disorders from happening in the future. For better accuracy, ensemble learning combines categories in ML models to make disease predictions [22]. As a result of looking at several articles, it summarizes the research on group techniques for diabetes, skin, kidney, liver, and heart diseases. It discovers that stacking usually gives the best results, especially for diabetes and skin diseases, followed by voting, bagging, and boosting. People's largest gland, the liver, breaks down food and drink, gets rid of toxins, and fights infections.

5.2 Severity Prediction and Mental Health Progression

Severity prediction and monitoring mental health progression are critical aspects of personalized psychiatric care, enabling clinicians to assess the intensity of symptoms and track changes over time. ML models play a pivotal role in identifying severity levels of mental health conditions such as depression, anxiety, and bipolar disorder by analyzing structured clinical data, self-reported questionnaires (e.g., PHQ-9, BDI), and unstructured data from speech, text, or wearable sensors. These models facilitate early detection of symptom escalation, support risk stratification, and guide timely interventions. By continuously evaluating patient progress, ML-driven systems enhance the ability to deliver adaptive, individualized treatment plans and improve overall clinical outcomes.

5.2.1 Depression Severity Prediction

Determining an individual's depression level is essential for predicting the severity of their depression and giving them with the right treatment. In terms of severity, different screening systems use different criteria. In contrast to the BDI's minimal, mild, moderate, and severe categories, the PHQ-9 employs light, moderately severe, and severe to classify depression [23]. The DSM-5 is usually used to diagnose depression as either present or absent, however self-screening tests like these are more popular for determining the degree of depression. Depression detection and severity prediction are comparable, but the latter has its own set of obstacles. Suicide and other co-occurring disorders are more common in those with severe depression, making this a pressing worry for them. Improving the efficiency and accuracy of severity prediction is an area where ML approaches can be quite useful.

5.2.2 Symptom Profile Concept

The identification of the relevance and heterogeneity of depressed symptoms is central to the concept of the symptom profile vector. It is important to examine symptom heterogeneity because it acknowledges the large range of symptom differences among individuals with depression [24]. Similar PHQ-9 assessment sum scores can indicate distinct symptoms in individuals. As a concept, "symptom significance" describes how different people place different weights on equally mundane symptoms. illustrates the suggested symptom-profiling approach's high-level pipeline. To begin, two separate subsets are created from the dataset. Every participant undergoes this partitioning on an individual basis; the data collected in the first month is used to create a symptom profile vector, and the data collected in subsequent months is used to evaluate the severity of depression.

5.2.3 Challenges and future direction with opportunities in mental risk health prediction

ML applications in mental health risk prediction face several critical challenges and limitations, including data scarcity, privacy concerns, and ethical issues related to algorithmic bias, informed consent, and the risk of stigmatization. These factors limit the development of robust, generalizable models and impede their deployment in diverse clinical and cultural contexts. Overcoming these challenges presents opportunities for advancement through the adoption of federated and privacy-preserving learning frameworks, which allow secure, decentralized model training on sensitive health data. The integration of Explainable AI (XAI) is essential to improve interpretability, transparency, and trust among clinicians and patients [25]. Additionally, incorporating causal inference techniques and personalized treatment prediction can enable more accurate and individualized mental health interventions. Future directions also include the use of mobile health (mHealth) platforms for scalable and continuous monitoring, as well as the development of multimodal and real-time emotion recognition systems to enhance dynamic, context-aware mental health risk assessments and support.

6 LITERATURE REVIEW

This literature review explores ML, NLP, and ensemble models for early mental health detection. Studies employ demographic, clinical, and social media data, improving diagnostic accuracy, accessibility, and empathetic digital care, addressing stigma and gaps in conventional mental health support systems.

Sharma et al. (2025) research ushers in a new era in multi-modal early diagnosis of mental illness disorders by combining data from speech and behaviour. By preparing and analyzing two distinct datasets, this method deals with missing values, normalizes data, and removes outliers. The proposed NeuroVibeNet aggregates behavioral data using a mix of IRF and Light Gradient-Boosting Machine (LightGBM). In order to process audio data, it employs a hybrid of SVM and K-Nearest Neighbors. Finally, a weighted voting technique is applied to consolidate the forecasts. With a precision of 99.06%, the proposed model surpasses the competitors when contrasting healthy and ill states. By validating the feasibility of multi-modal data integration, this paradigm paves the way for reliable and early detection of mental disease [26].

Cruz-Gonzalez et al. (2025) explores into the application of AI in the field of mental health, including tracking, diagnosing, and intervening. After searching CCTR, CINAHL, PsycINFO, PubMed, and Scopus from February 2024 to beginning, 85 studies were found that fulfilled the inclusion criteria. The most common AI techniques employed were ML for monitoring, SVMs and RFs for diagnoses, and chatbots for intervention. It felt like AI worked well at diagnosing mental health conditions, classifying them, predicting risks, treatment responses, and ongoing prognoses [27].

Negandhi et al. (2024) present a system that uses ML to identify and evaluate mental health disorders early on, so that help may be provided when needed. In addition, by providing a confidential and non-judgmental digital evaluation method, it helps lessen the shame that comes with seeking help for mental health issues. The study describes the system's features, which include an easy-to-navigate user interface, standardised tests for different diseases, subjective questions with audio-based replies to improve the accuracy of diagnoses, and a special "Attention Monitoring Game" for people who suffer from Attention Deficit Hyperactivity Disorder [28].

Supriya et al. (2024) study has proposed an experimental methodology that uses publicly available Reddit data in developing a mental health diagnosis system. The techniques of NLP are used to make the machine comprehend the social media posts generated on Reddit, and generalized DL and ML algorithms are trained to distinguish the social media text into one of the aforementioned four mental disorders: depression, anxiety, schizophrenia, and bipolar. The relative analysis of these models is conducted and the results displayed that random forest compared to other models was better with the program achieving an accuracy of 90 percent [29].

Sharma, Kalra and Sukhija (2024) application of ensemble methods to improve mental disease diagnosis and evaluation is the main topic of this work. There are significant obstacles to identifying mental health disorders using conventional methods because of the subjective and complicated character of these conditions, which can lead to incorrect or delayed diagnoses. In this study, apply an ensemble model based on three advanced ML algorithms LR, RF, and Gradient Boosting Classifier to show how psychiatry and psychology can benefit from ML in terms of improved diagnosis and treatment planning. Genetic, neurological, digital biomarker, clinical, and behavioural patterns are only some of the data sets that can be used to improve diagnostic accuracy through the use of the ensemble model, an analytical tool that finds that variables aggregated into complex forms boost accuracy [30].

Poonam et al. (2024) provide a high-level overview of the most well-known quantum-enhanced ML algorithms, including QKNN, QSVM, and VQC, based on the literature review conducted over the last decade. Negative impacts on mental health and an increased risk of several diseases may result from chronic stress. This effort primarily aims to assess knowledge workers' ability to forecast their degree of job stress using several modalities of quantum augmented ML [31].

Etika, Progga and Khan (2024) study will completely change the mental health care system by addressing important gaps in the field and making help available to everyone for free. An innovative chatbot that responds to people's emotional needs, such as diagnosing issues and offering timely guidance, and cutting-edge technologies for early detection of mental health illnesses have been integrated into a centralized platform's dynamic website. Solutions for mental health care accessibility are being developed through the integration of early detection models of mental health issues with a compassionate chatbot that reacts to individuals according to their unique emotional requires [32].

Bajaj et al. (2023) main objective of research is to develop a model that can predict when an individual might require medical assistance for mental health concerns. The model will be built using a mix of demographic and clinical data, including medical records, survey findings, and health-oriented online communities. Additionally, self-reported symptoms will be included. Information for this study will come from a variety of sources, including medical records, survey results, and data collected from community health forums online. The model will be tested using industry-standard metrics and subjected to cross-validation to guarantee its accuracy [33].

Table 1 presents recent studies on AI and ML-driven mental health diagnosis and support systems, highlighting approaches like NLP, ensemble models, quantum ML, and AI chatbots, along with their key outcomes, existing challenges, and potential future enhancements.

Table 1: Summary of the smart fintech ecosystem with AI, ML and blockchain technology

Reference	Study On	Approach	Key Findings	Challenges	Limitations
Sharma et al. (2025)	The use of a multi-modal AI framework for the early diagnosis of mental illness	Data preparation for both spoken and behavioral forms: IRF with LightGBM for behavioral data, Hybrid SVM with KNN for spoken form data, and weighted voting for prediction fusion.	Proven efficacy of multi-modal data integration; reached 99.06% accuracy in identifying normal from diseased states	Complexity in synchronizing and preprocessing multi-modal data-Ensuring real-time applicability	Limited to binary classification (normal vs pathological), May not generalize across diverse populations
Cruz-Gonzalez et al. (2025)	uses of AI diagnosis, tracking, and treatment	- Systematic review of 85 studies from multiple databases- ML methods: SVM, Random Forest, AI Chatbots for interventions	AI tools are accurate in diagnosis and prognosis prediction, AI chatbots show promise for intervention and treatment personalization.	Heterogeneity of studies reviewed-Different metrics and validation strategies across studies	Lack of standardization - Many studies lack clinical validation, and There Are Ethical and privacy concerns in AI usage.

Negandhi et al. (2024)	ML-powered tool for the early diagnosis of psychological disorders	Intuitive UI, standardized quizzes, audio-based subjective answers, ADHD-specific attention game	Enables private, non-judgmental assessment and early intervention	Requires accurate self-reporting and user engagement for reliable outcomes	Enhance AI-driven diagnostic precision via multimodal inputs (text, audio, behavioural patterns)
Supriya et al. (2024)	Centralized AI platform for mental health detection and support	Web-based platform with early detection models + empathetic chatbot for emotional support	Offers free, accessible, timely support for individuals lacking therapy access	Balancing AI-driven responses with empathetic, context-sensitive interactions	Integrating sentiment-aware AI chatbots with personalized mental health intervention models
Sharma, et.al. (2024)	Mental health diagnosis via social media data (Reddit)	NLP and ML/DL models classifying posts into depression, anxiety, schizophrenia, bipolar	Random Forest achieved 90% accuracy outperforming other models	High variability in user-generated text; difficulty in context understanding and labeling	Expand to multimodal social data (images, speech) and context-aware NLP models.
Poonam et al. (2024)	Ensemble ML for mental health diagnosis	Combined Logistic Regression, Random Forest, Gradient Boosting Classifier analyzing genetic, clinical, digital biomarkers.	Ensemble models improved diagnostic accuracy by identifying complex variable combinations	Subjectivity and complexity of mental illness data, delayed or incorrect diagnoses with conventional methods	Integrating ensemble models with explainable AI for transparent clinical decision support
Etika, et al. (2024)	Quantum-augmented ML for stress level forecasting	VQC, QKNN, QSVM explored for workplace stress prediction	Potential of quantum-enhanced ML in improving stress-level forecasting through multimodal data	Immaturity of quantum hardware; scalability of algorithms in real-world applications	Hybrid classical-quantum pipelines for scalable, real-time mental health monitoring
Bajaj et al. (2023)	Predictive model for mental health medical treatment need	ML model built on demographic, clinical, and self-reported data from varied sources; cross-validation used	Demonstrated reliable prediction of need for medical treatment using mixed datasets	Data heterogeneity, missing values, and privacy concerns in compiling multi-source datasets	Integrating federated learning and secure data aggregation for privacy-preserving mental health analytics

7 CONCLUSION AND FUTURE SCOPE

ML models are increasingly applied in mental health to diagnose psychological disorders and predict associated risks. These models analyze complex clinical, behavioral, and social data patterns, aiming to improve early detection, personalized care, and mental health risk management strategies. This paper examined supervised, unsupervised, and reinforcement learning approaches, highlighting their applications in clinical practice. In mental health care, ML models such as KNN, SVM, CNN, and LR have been extensively used for the diagnosis, classification, and symptom severity prediction of mental disorders. Risk prediction models utilizing demographic, clinical, and genetic data further support early intervention and personalized care.

The accuracy of predictions and the interpretability of models can be improved by using multimodal data sources in future research. These sources could include social media activity, wearable devices, and electronic health records. When it comes to implementing healthcare systems in the real world, tackling issues such as data privacy, model bias, and clinical explainability is absolutely crucial. Further research is needed to develop dynamic, personalized ML models that adapt to individual mental health profiles over time. The integration of explainable AI (XAI) and reinforcement learning frameworks could further advance autonomous decision-making, symptom profiling, and personalized care strategies in mental health management.

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