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DETECTING AND TREATING MENTAL HEALTH CONDITIONS USING BERT AND SVM

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ABSTRACT

Mental health disorders are becoming a bigger problem for public health around the world. They hurt people's emotional health, cognitive functioning, and overall quality of life. There are problems with traditional mental health care systems, like delayed diagnosis, subjective assessment, poor scalability, and limited access to trained professionals. Artificial Intelligence (AI) has become a promising way to deal with these problems in the last few years. It does this by making it possible to use data- driven, objective, and scalable methods to find and treat mental health issues. The study investigates a diverse array of AI methodologies, encompassing machine learning, deep learning, and natural language processing, and analyzes their applicability to mental health-related textual data. We do exploratory data analysis to find out how sentiment is spread out, how often words appear, and how the length of the text changes. We use feature extraction methods like Bag-of-Words and TF-IDF, and we test baseline classification models like Support Vector Machine (SVM) and BERT-based models using standard performance metrics like accuracy, precision, recall, F1-score, confusion matrices, and learning curves. The results show that AI-based models can tell the difference between different types of feelings and mental health problems. Classical machine learning models are especially good at what they do and work quickly, while deep learning models are better at handling larger datasets. The results of this study show that AI tools can greatly improve the detection and treatment of mental health issues when they are made and used in a responsible way.

Keywords: Artificial Intelligence, Mental Health Detection, Sentiment Analysis, Machine Learning, NLP, SVM, BERT.

1. INTRODUCTION

Artificial intelligence (AI) could really help the field of mental healthcare. AI could make mental health services easier to get and more useful by adding things like early diagnosis of mental health problems and personalized treatment plans. At the moment, people are making AI systems for a lot of different purposes, like keeping an eye on mental health, doing diagnostic tests, helping with therapy (like chatbots), and providing educational resources to help people learn more about mental health. These apps can be used for a wide range of things, both in clinical and nonclinical settings. Some of these are medical issues like depression and anxiety, while others are more personal, like feeling alone. We can better understand these complexities by putting AI applications in mental health care into groups based on their main goals: screening, monitoring, diagnosis, therapy, and education. Machine learning or natural language processing (NLP) is often used by screening technologies to find signs of mental health problems in data from social media, smartphone use, or medical records [1]. Wearables and other monitoring devices record biometric or behavioral data in order to spot trends that could indicate a change in mental health. A variety of data sources, including neuroimaging and speech pattern analysis, are used by diagnostic tools to aid in the identification of mental health disorders. Two common examples of mental health treatment applications are emotion detection software for various exposure therapies and AI-driven chatbots for the cognitive behavioral therapy (CBT) [2]. This study overviews and examines these challenges using Smuha's (2021) typology of individual, communal, and societal damages as a foundational driving force and suggests solutions through a multi-level risk analytical framework [3]. This article aims to offer solutions for the ethical incorporation of AI into mental healthcare by analyzing these issues from multiple perspectives, ensuring the enhancement of patient health while safeguarding individual rights, societal interests, and values.

AI is changing psychiatry in a big way. It makes personalized, data-driven treatment plans viably possible that are inevitably better than the old trial-and-error methods used historically [13].

In pharmacopsychiatry, machine learning models incorporate clinical, genetic, and neuroimaging data to improve dosage precision, mitigate adverse effects, and forecast drug responses [5]. AI-driven polygenic risk scores integrate genomic and clinical data to forecast the efficacy or adverse effects of a medication. Pharmacogenomic markers, such as cytochrome P450 polymorphisms, are utilized in the selection of antidepressants and antipsychotics [6]. There are

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also problems with making data consistent, making sure everyone is fairly represented, and using the results in everyday practice, but these methods hold a lot of promise for treating depression that doesn't respond to treatment [7]. AI is also helping in envisioning an enhanced psychotherapy relying on adaptive digital technology. Two common examples of chatbots based on cognitive behavioral therapy (CBT) that offer real-time, scalable and dependable help are cognitive reframing and journaling prompts [8].

Figure 1: Different types of mental health detection and management approaches [4].

Therapists can keep an eye on their clients' emotional patterns over time and change how they work with them as needed by using these methods. With their help, people in low-income neighborhoods don't have to worry about things like shame, cost, and lack [11, 12]. There are real concerns about data privacy, algorithmic bias, and a lack of human empathy, but it's encouraging to see that these systems could make traditional treatment more engaging and easier to get [9]. Artificial intelligence (AI) is changing the way mental health diagnoses are made by making it easier to find patterns in large amounts of different types of data that could point to different diseases. "This area mainly uses AI techniques like Deep Learning (DL), Natural Language Processing (NLP), and Machine Learning (ML), each of which is good at processing different types of data [10]."

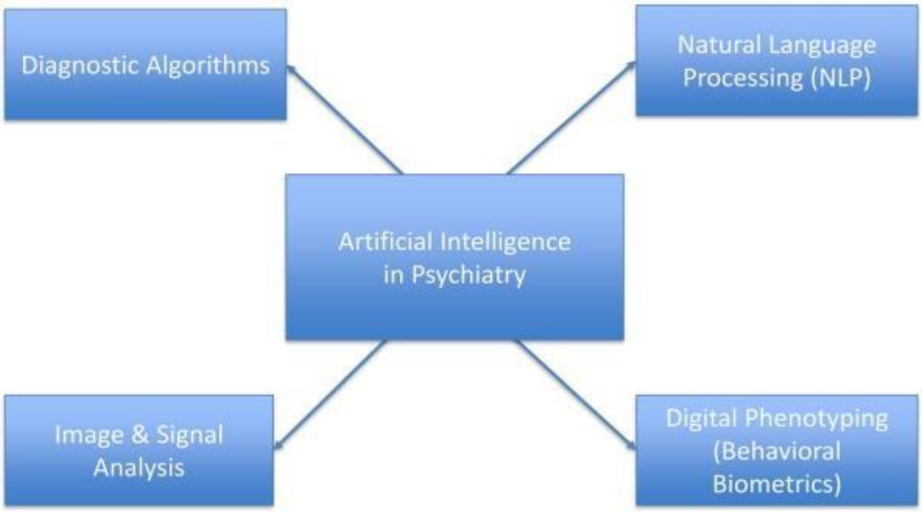

Figure 2: Key domains of AI in psychiatric diagnosis [11]

Mood, cognitive, and sleep data integrated with standard approaches outperforms them in improving the accuracy of diagnosing severe depressive illness, according to studies such as those from the Predictive Analytics Competition [15]. While these systems have the potential to lessen diagnostic bias and provide consistent second views, underrepresented groups may find it difficult to rely on them since their accuracy is dependent on the quality and diversity of the data used to train them [16].

To this day, artificial intelligence models have been developed for the diagnosis of a broad variety of diseases. Through the use of many types of data, such as medical photos, medical texts, genetics, medical talks, EEG, and ECG, these models have been subjected to the process of architectural planning and fine-tuning [14]. These methods can be used for things like diagnostic categorization, finding phenotypes, and other things that have to do with diagnosing illness. The main goal of this research paper is to look into how artificial intelligence-based tools can help find and treat mental health problems. The focus is on making diagnoses more accurate, tailoring treatments to each patient, and improving the overall delivery of mental health care. In order to achieve this aim, the study focuses on evaluating the effectiveness, applicability, and limitations of various AI techniques used in mental health assessment and intervention.

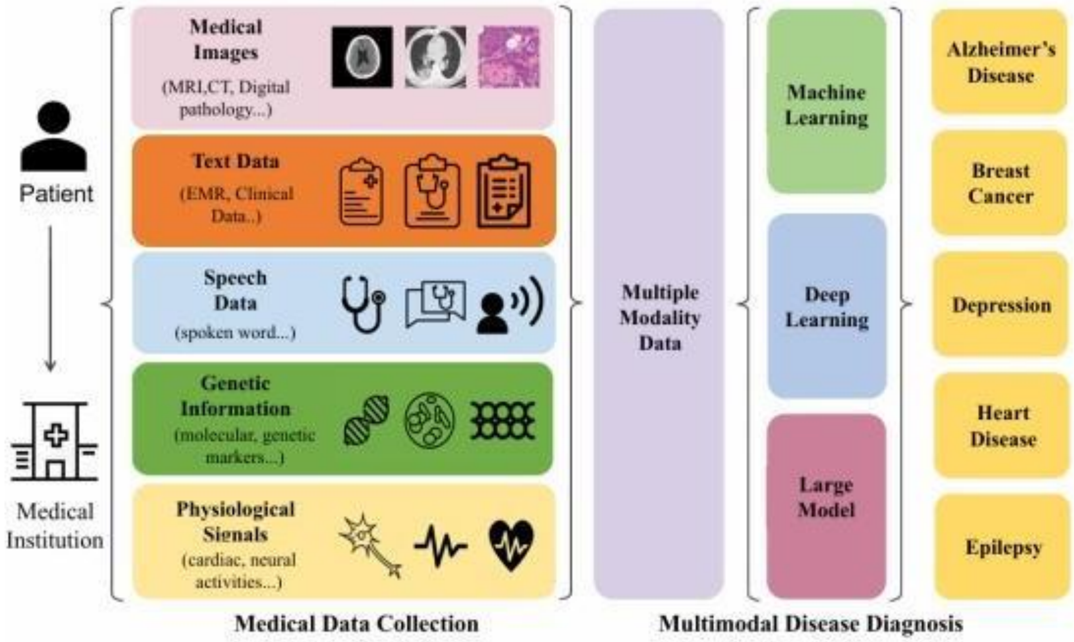

Figure 3: "The diverse data types including images, speech, text, and genetic information can be produced in the clinical diagnostic process" [17].

2. LITERATURE REVIEW

(Momand et al., 2025) [1], Utilizing behavioral data alongside biological indicators (biomarkers) may enhance diagnostic precision for mental health disorders such as bipolar disorder, anxiety, and depression. This study examines predictive modeling tools that accomplish precisely that. We investigate the potential for integrating physiological data (e.g., EEG, HRV) with behavioral indicators (e.g., speech patterns, social activity, digital footprints) using supervised learning models. The results demonstrate that AI models exhibit significantly enhanced performance when trained on integrated multimodal datasets for mental health status classification, showing improved sensitivity and accuracy across a diverse array of patient characteristics.

(Atlam et al., 2025) [2], This study highlights that there is a serious lack of interpretability in the existing models used to diagnose mental health problems (MHD). A strong framework that uses Explainable Artificial Intelligence (XAI) and machine learning algorithms to detect mental health issues in toddlers and other young children is presented in this paper as the Explainable Mental Health issues (EMHD) model. One of the primary parts of the EMHD is the ensemble model, and the other is the Explainable AI (XAI)." Prior to classifying the MHD dataset, an ensemble model called Voting is used. This model employs many feature selection strategies, including Mutual Information (Mutinfo), Analysis of Variance (ANOVA), and Recursive Feature Elimination (RFE). "To further explain and clarify the model's decision-making process, XAI is secondly included into the suggested framework.

(Gautam et al., 2025) [18], Early identification and intervention strategies for mental health disorders ought to be more astute, scalable, and uncomplicated. This research, which was powered by full-stack AI, was mostly about an online app that lets people report their own mental health. Ashgen is an interactive and conversational deep learning-based chatbot that helps users talk to each other and gives them advice. It also makes the system more interesting and uses the SVM model to guess a user's mental health based on a cleaned and encoded mental health dataset and data that the user reports themselves. The program uses MySQL to keep track of user data. To keep user data safe, werkzeug.security was used to hash the password. This helps to check that users are who they say they are without hurting their privacy. The study shows how augmented mental health systems that use intelligent automation and emotional support can work together.

(Khedikar et al., 2025) [19], "The suggested method makes use of artificial neural networks (ANNs) to sift through complex and multidimensional data pertaining to mental health, such as reactions expressed in text, physiological signs, and patterns of behavior. By requiring users to register and authenticate themselves, MindFit takes care of the first issue, the significance of mental health in hectic lives and guarantees the safety of those seeking mental health evaluation and assistance. The self- assessment tool allows users to keep tabs on their mental health and get a personalized perspective." To further educate consumers about mental health, MindFit offers selected material including inspiring films and educational articles.To further assist its customers in finding the help they need, MindFit offers suggestions and links to mental health specialists.

(Sahani et al., 2025) [20], Because traditional methods can't keep up with the growing need for mental health care, new ideas have come up, like using AI in basic mental health therapy. This study shows that AI could make healthcare easier to get by making it easier to find people and giving each person their own treatment. AI can be used in the real world to combine electronic medical records (EMRs), figure out how people feel, recognize voices, and see facial expressions. BrainCare is another AI program that uses physiological and behavioral data to keep an eye on health online. People believe that mental health care is a group effort that happens all the time. The psychic web method protects people's privacy while still giving them information. This article also talks about the problems and opportunities that lie ahead for using AI in healthcare, since it could help people with mental health issues all over the world.

(Rony et al., 2024) [11], Diagnosis for Autism spectrum disorder (ASD) is difficult because there are so many symptoms and skill levels, so it needs to be done in several ways. This study enhanced the accuracy and consistency of autism spectrum disorder diagnosis through advanced machine learning techniques. A standard dataset of 20 variables and 1054 patient samples was used. Data mining (DM) visualization methods including Chi-Square testing, analysis of variance, and correlation analysis helped researchers uncover relevant variables. Outliers were removed during preprocessing to strengthen the model.Based on logistic regression (LR) and Shapley additive explanations, the DMLRS model is 99% accurate, surpassing the best approaches. Shapley Additive Explanations' explainable AI simplifies it.

(Olalekan John Okesanya et al., 2025) [21], The use of AI in mental health is quickly changing the way mental health services are provided, including diagnosis, risk classification, treatment customisation, and more. Recent studies on the ethical implications, methodological hurdles, and real-world uses of artificial intelligence in psychiatry were included in this narrative review. Finding peer-reviewed publications and grey literature pertaining to AI integration in psychiatry required a thorough literature search that did not restrict search results by publication year. PubMed, Scopus, Web of Science, and Google Scholar were used for this purpose.

(Omiyefa, 2025) [22], By using AI and ML to improve precision, efficiency, and customization, precision mental health is revolutionizing conventional psychiatric diagnoses and treatment paradigms. The subjective nature of traditional mental health examinations increases the likelihood of misdiagnosis and postpones treatment. The emergence of AI-powered models tackles these issues by offering objective and predictive understandings of mental health disorders via the use of neuroimaging, behavioral analytics, and massive databases. Using speech patterns, facial expressions, and physiological indicators, advanced machine learning techniques, such as deep learning and natural language processing (NLP), allow for automated screening, early disorder identification, and real-time symptom monitoring.

(Mansi Khare, 2024) [23], Artificial intelligence (AI) has emerged as a powerful tool for psychiatric patient management in this technological age. The use of AI has led to the diagnosis and treatment of several mental diseases in recent years. A fresh viewpoint on mental diseases is offered by new innovation such as sensor-based systems, Deep Learning (DL), Machine Learning (ML), and robotics. The use of artificial intelligence (AI) to the diagnosis and treatment of mental diseases was summarized in this narrative review article. The use of AI in the fields of prognosis, clinical diagnosis, management treatment, and the resolution of clinical and technical concerns may greatly benefit patients suffering from mental illnesses.

(Hossain et al., 2025) [24], The impact of mental health illnesses on a person's and society's capacity for rational thought, emotional regulation, and social cohesion are far- reaching and long-lasting. The need for creative responses to the growing worldwide crisis in mental health is pressing, and sentiment analysis is showing great promise as a tool for the early detection and treatment of mental health issues. The intricacy of writings pertaining to mental health, with their specialized vocabulary and domain-specific subtleties, limits traditional techniques. "In response to these difficulties, we present BERT-Fuse, a hybrid deep learning model that integrates state-of-the-art neural architectures such as Bidirectional Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Transformer blocks, and Convolutional Neural Networks (CNN) with more conventional feature extraction methods using TF-IDF and Bag-of-Words. With BERT embeddings, they obtained the best results in terms of accuracy, precision, recall, and F1-score, outperforming GloVe and FastText, two other word embedding approaches used inside BERT-Fuse."

(Swathi Gowroju, 2025) [25], A state-of-the-art digital mental health support platform, MindBridge aims to provide affordable, simply accessible, and individually tailored emotional care. "Online therapy recommendations, emotional analysis, and virtual support groups are all available to users of the platform thanks to state-of-the-art technology including Edge Computing, Machine Learning, and Natural Language Processing (NLP). Connecting individuals with mental health professionals, MindBridge offers support via mobile devices and web browsers. Automated sentiment analysis, symptom severity evaluation, and personality disorder diagnosis made possible by state-of-the-art machine learning models like BERT models.

3. METHODOLOGY

This Kaggle dataset contains 52,681 text samples with status labels indicating mental health diseases and emotional or psychological states. The dataset was created using expert mental health statistics, social media postings, and conversation data to cover a broad spectrum of mental health conditions. Informal language, typing errors, minor psychological indications, anxiety signals, and popular sayings result from the text samples' varying durations and difficulty levels.

This massive and diversified dataset is the gold standard for mood and mental health classification. AI-based early warning systems, psychological assessment tools, and automated mental health monitoring are enabled by it. Exploratory data analysis (EDA) helped us identify problems, patterns, and trends and understand our most critical data. Figure 6 shows all mental health state labels and mood orientations in this study's dataset. Image contains two parts: Figure 6(a) depicts mental health problems and Figure 6(b) exhibits positive, negative, and neutral overall sentiments. These graphics reveal the dataset's composition, equilibrium, and other similarities to other data points. This impacts model training and testing.

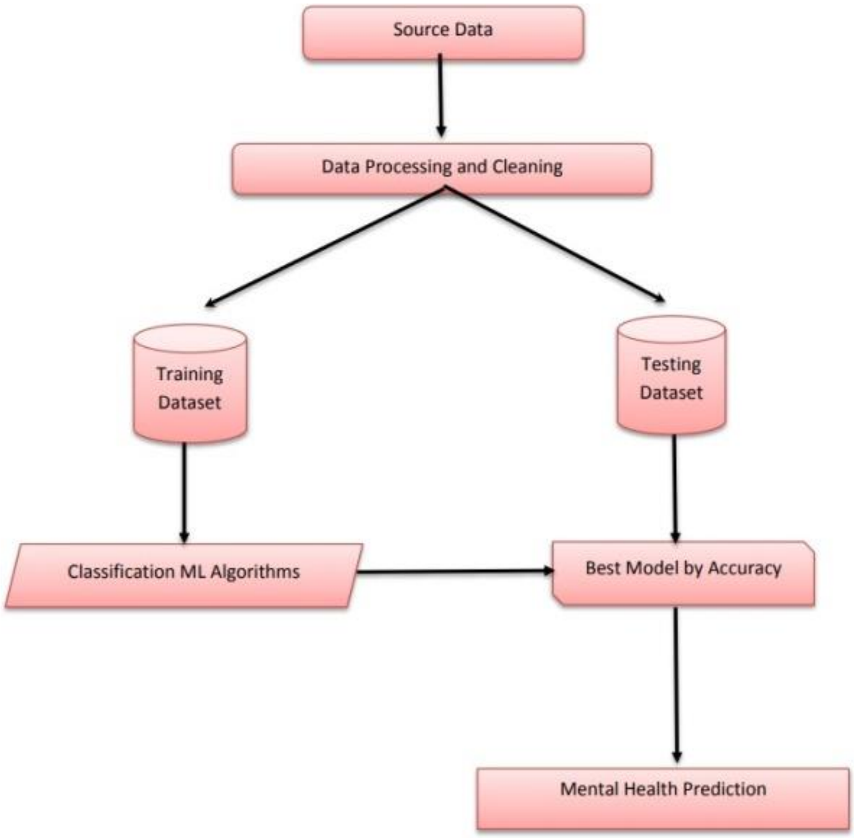

Figure 4: Work flow diagram

During the process of developing the system, needs are gathered. These are the needs that need to be addressed.

1. Functional requirements
2. Non-Functional requirements
3. Technical requirements

A. Hardware requirements
B. Software requirements

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1. Functional requirements

In terms of technical details, the software product's needs are laid forth in the software requirements specification. In requirements analysis, it is the first stage. A software system's needs are detailed in it. Here are the specifics of using libraries like as sk-learn, pandas, numpy, matplotlib, and seaborn.

2. Non-Functional Requirements

Process of functional steps:

I. Problem define
II. Preparing data
III. Evaluating algorithms
IV. Improving results
V. Prediction the result

3. Technical Requirements

Software Requirements:

- Operating System : Windows
- Tool : Anaconda with Jupyter Notebook Hardware requirements:
- Processor : Pentium IV/III
- Hard disk : minimum 80 GB
- RAM : minimum 2 GB

To get a more sophisticated depiction, "we used the BERT tokenizer included in the Hugging Face Transformers package." The "bert-base-uncased" model [15] was used to train the tokenizer. "In order to convert the text into numbers, token IDs and attention masks were used. In order to make sure that the input dimensions were consistent, larger sequences were cut to 80 tokens and shorter ones were filled in with special tokens at the beginning and the end." Structured inputs suitable for the processing pipeline of the BERT model were produced by use of attention masks that distinguished between significant tokens and padding items [26].

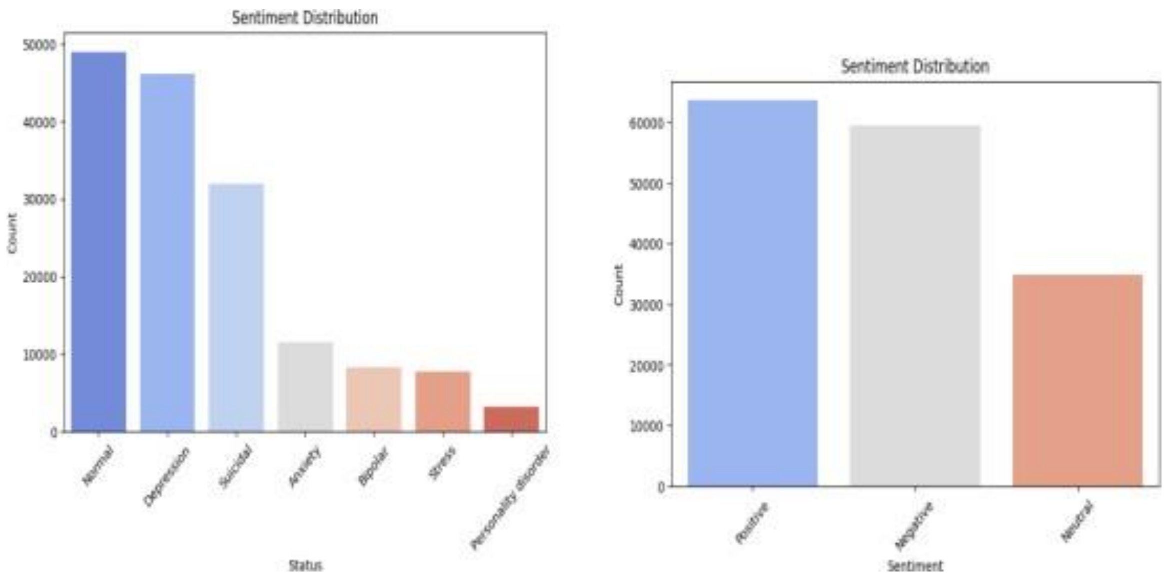

Figure 5: Status and sentiment distribution of the mental health dataset.

Table 1: "Sentiment classification breakdown across psychological conditions"

Status	Negative	Neutral	Positive
Anxiety	5264	1302	4957
Bipolar	3150	243	4938
Depression	21563	3504	21145
Normal	8228	26548	14253
Personality disorder	1340	181	1710

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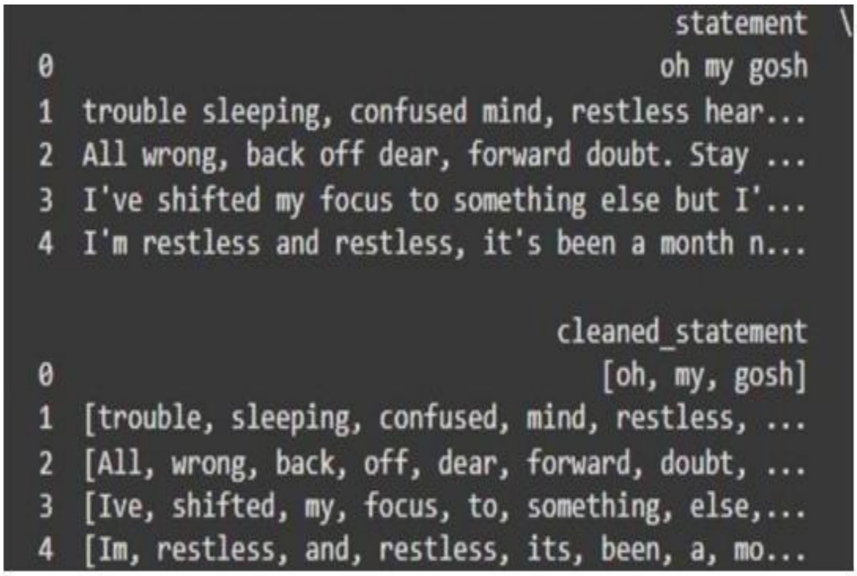
Stress	3565	379	3817
Suicidal	16290	2726	12940

Table 1 presents a detailed sentiment classification breakdown across different psychological conditions in the dataset, categorizing textual instances into Negative, Neutral, and Positive sentiment classes for each mental health status. This table provides important insight into how emotional polarity varies across psychological conditions and helps in understanding the linguistic and emotional characteristics associated with each category.

Tools and Techniques Used: Support Vector Machine (SVM) and BERT (Bidirectional Encoder Representations from Transformers).

4. RESULTS AND FINDINGS

After data cleaning, the data was split in half: 80% for training and 20% for testing, after the cleaning of the text. By using this data, the BERT-SVM and SVM models were then trained and evaluated. The evaluation was carried out using F1-score, recall, accuracy, and precision, which are frequently used metrics for assessing the performance of classification models.



```
                                           statement  \
0                                         oh my gosh
1  trouble sleeping, confused mind, restless hear...
2  All wrong, back off dear, forward doubt. Stay ...
3  I've shifted my focus to something else but I'...
4  I'm restless and restless, it's been a month n...

                                   cleaned_statement
0                                      [oh, my, gosh]
1  [trouble, sleeping, confused, mind, restless, ...
2  [All, wrong, back, off, dear, forward, doubt, ...
3  [Ive, shifted, my, focus, to, something, else,...
4  [Im, restless, and, restless, its, been, a, mo...
```

Figure 6: Data cleaning

Table 2: Baseline performances comparison

Model	Augmentation	Training Accuracy	Val Accuracy	Test Accuracy	Precision	Recall	F1-score
BERT	Yes	67.29 %	78.57 %	78.48 %	80.64 %	78.47 %	79.34 %
	No	57.18 %	72.88 %	72.83 %	72.78 %	75.21 %	73.47 %
SVM	Yes	99.01 %	96.82 %	97.15 %	97.28 %	97.17 %	97.52 %
	No	96.47 %	91.87 %	91.66 %	92.87 %	92.36 %	92.60 %

Table 2 shows how important data augmentation is for both methods to make the model work better. More importantly, it shows that the SVM model does much better than the BERT baseline in this experiment and with this feature representation. These findings validate the choice of SVM as a robust baseline and encourage additional investigation into hybrid or advanced deep learning architectures for enhanced mental health sentiment classification [27].

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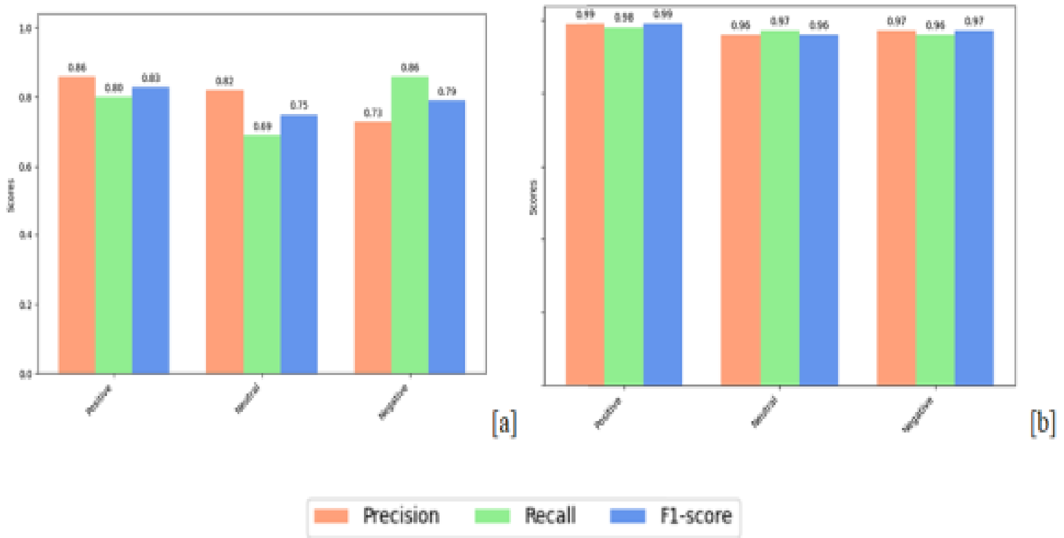

Figure 7: Class-wise baseline comparison of [a] BERT and [b] SVM model.

Figure 7 shows that the SVM model is better than the BERT baseline at class-wise sentiment classification. While BERT shows acceptable performance, especially for positive and negative sentiments, its inconsistency across classes and lower recall for neutral sentiment limit its effectiveness. The SVM model, on the other hand, delivers uniformly high precision, recall, and F1-scores, indicating strong generalization and reliable sentiment discrimination. These findings reinforce the earlier baseline comparison results and justify the selection of SVM as a highly effective baseline model for mental health sentiment classification in this study [28].

Figure 9 highlights the contrast between the two models. The BERT model works pretty well, but it has a harder time telling the difference between Neutral and Negative feelings, which makes it less reliable for classification. The SVM model, on the other hand, has a strong diagonal dominance in all classes, which means it is very accurate and not very confusing. These results back up the earlier comparisons of performance and show that SVM is better at classifying sentiment for the mental health dataset used in this study [26].

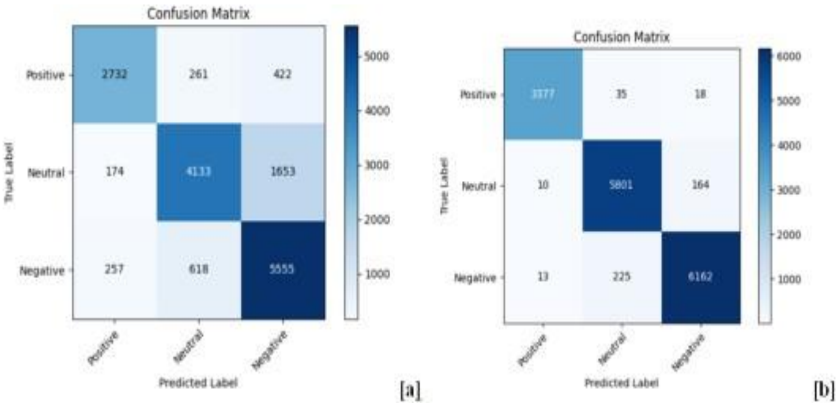

Figure 8: Confusion matrices for sentiment classification using [a] BERT and [b] SVM model.

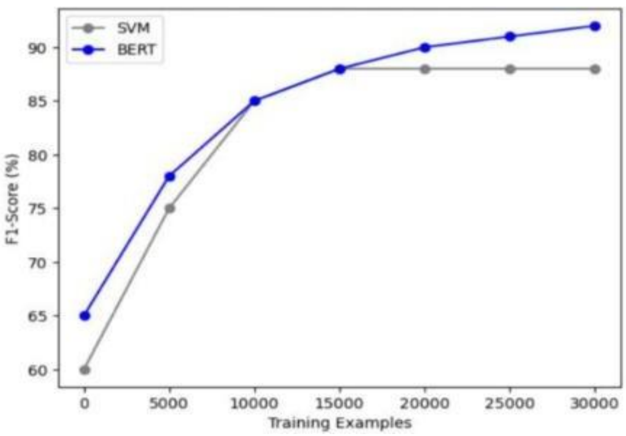

Figure 9: Learning Curves for SVM and BERT Model

Figure 10 shows that the SVM model works very well and uses less data when the dataset is medium-sized, but it stops working as well as the BERT model sooner. BERT uses more resources at first, but it scales better and keeps getting better as the training sets get bigger. These observations show the trade-off between classical machine learning and deep learning methods for classifying mental health sentiment. The choice of model may depend on the amount of data available, the computational resources available, and the desired performance ceilings [29].

5. CONCLUSION

Text, audio, behavioral patterns, physiological signs, and digital footprints were used to test AI methods including machine learning, deep learning, and natural language processing on mental health data. This thesis shows that AI-based sentiment and mental health categorization methods work experimentally. Representing real-world mental health conversation, the dataset showed considerable emotional and linguistic variation.

Sentiment distribution, word frequency, TF-IDF relevance, and word count variability analysis illuminated dataset properties and drove feature engineering choices. These investigations showed that strong mental health categorization models must address class imbalance, varying text lengths, and emotionally expressive language. Comparing baseline models revealed technical insights. “Classical machine learning approaches as per the analysis particularly Support Vector Machines (SVM), demonstrated strong and consistent performance across multiple evaluation metrics, including accuracy, precision, recall, F1- score, and confusion matrices, and Learning curve.” In contrast, transformer-based models such as BERT showed competitive performance but exhibited greater sensitivity to data distribution, class overlap, and computational constraints. The class-wise and threshold-based evaluations clearly indicated that while deep learning models benefit from large-scale data and contextual representations, well-engineered classical models can achieve superior or comparable performance in structured sentiment classification tasks under constrained settings [30].

One important area for future work is the integration of multimodal data sources. The present study predominantly emphasizes textual data for sentiment and mental health classification. But mental health issues are inherently complex and can't be fully described with words alone [31]. In the future, systems will be able to combine speech signals, facial expressions, physiological indicators (like heart rate variability and sleep patterns), data from wearable sensors, neuroimaging outputs, and behavioral metrics from smartphones.

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