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Integrating Multimodal Data with CNN and LSTM Models: A Paradigm Shift in Mental Health Diagnostics

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ABSTRACT

It is not surprising that mental health disorders are not simple and may need multiple forms of data to diagnose and treat the patient. In this paper, a promising concept of quantifying mental health disorder symptoms through the fusion of multiple modalities using CNNs and LSTMs is described. CNNs are particularly effective in recognizing spatial characteristics that can be extracted from picture data, be it a MRI image of the brain, a facial expression or a person's gesture, for instance, while LSTMs are quite successful in recognizing temporal patterns within time series data, such as in speech and signal processing, or in behavioural and physiological data over time. The proposed method is more comprehensive and dynamic since the two classes of deep learning models are integrated to estimate the severity of the mental health problem. As a research question, we propose the concept of how fMRI images, audios, and heart rate variability can be used together to improve the process of recognizing people's mental states. It is proposed that the signs related to spatial features of data and temporal groups be identified through CNNs for spatial feature extraction and LSTMs for temporal sequence analysis, the system can provide more accurate predictions and for different mental health states, including depression, anxiety, and PTSD. This research seeks to show that the application of deep learning could improve the diagnosis of mental health disorders, and tailor treatment to patient preferences. The findings of the following study demonstrate enhanced accurate diagnoses, which indicate a bright future for AI-based treatment of mental disorders.

Keywords: *Multimodal Data, CNN, LSTM, Mental Health Diagnostics, Deep Learning, Mental Health Disorders*.

1. INTRODUCTION

Common DHM include depression, anxiety, schizophrenia, as well as PTSD, which are found in millions of patients across the globe contributing to personal and social costs. Pre-existing diagnostic approaches are based mostly on interview, questionnaires, and behavioral observations, and while important, they suffer from indirection and imprecision concerning newer and more effective therapeutic techniques. These methods are entirely qualitative that depend on the performance of the patient, predisposing factors such as social prejudices or mood variations can affect the results leading to wrong diagnosis or delayed treatment. In addition, mental health check-ups are usually reductions of the disorder by concentrating much of the investigation on particular symptoms and with little regard to the interaction between behavioral[1], physiological, and cognitive facets of the disease. Consequently, new methodologies have been investigated in order to draw a more exhaustive picture of the state of the patient, among which the fusion of multimodal data is one of the most promising. Multimodal data mostly derived from speech (intensity and tone), gesture (eye, face and body movement) and text (spoken and written words), physiology (heart rate, electroencephalogram or fMRI scans). This approach makes sense because one can use different data to capture a compendium of patient's mental state in contrast to the restricted set of emotions and moods that may be covered by standard questionnaires or inventories. For example, speaking rate can indicate a patient's mood or cognitive status, while the physiological measurements may indicate, for example, sympathetic nervous system activity associated with stress or anxiety. Extensions of such approaches include fMRI that also supplies location information regarding mental health related cognition Unlike conventional machine learning methodologies, deep learning approaches have brought significant changes in the analysis of multimodal data. From the described types of data, two outstanding architectures are Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks[2]. CNNs are a versatile tool for obtaining spatial features for data analysis including pictures, as well as the diagnostics of the brain scans or facial expressions that may indicate mental disorders. LSTMs on the other hand is used to model dependencies in the sequence, therefore used to model speech or physiological signals over time. When two definitions of CNNs and LSTMs are integrated, spatial features and sequential properties of mental health assessment data can be learned simultaneously, improving diagnostic results and overall system reliability. The purpose of this paper is to show that the use of multimodal data which are analysed with CNNs for extraction of spatial features and LSTMs for temporal sequence analysis can fundamentally redefine mental health diagnosis. This approach will help to enhance identification accuracy and the possibility of early diagnosis of the mental-state patient and carve out an individual treatment plan based on plentiful knowledge of a patient's condition. Our work here seeks to demonstrate that integration of CNNs and LSTMs is a new paradigm shift within this domain as opposed to the traditional style archives that focus on specific mental disorders.

2. RELATED WORK

Mental health diagnosis has for many years used interview, questionnaire, and behavioral observations. Although these methods are critical, they possess built-in drawbacks. Inspection and listening involves observation and this involve clinical interviews which are always subjective hence depending with the kind of relationship the clinician has with the patient. Patients enrolled in the study may fail to give accurate information about their conditions; since some conditions are deemed as voluntary or socially disliked, patient may down- or over-play their conditions. Further, these tools are poorly oriented in no specificity and shortcomings of mental health disorders[3] that are sometimes manifested not only emotionally but also cognitively and physiologically. For that reason, the great majority of patients suffers from mis diagnostics or receives optimal treatment when it is already too late, thereby contributing for suboptimal results.

In response to these problems, diagnostic tools of mental health disorders have incorporated utilization of the ML and AI. These technologies have advanced in the analysis of multimodal data that involves combining sources of information such as audio, video, text and physiological information. Advantages of using machine learning models include the capability to process large amount of data and extract and make predictions with much precision than conventional methods. One of the well-known strategies is the data fusion methodologies which encompasses such types of data to compile a wider and more realistic view of a patient's state of mind. For example, audio data, for example, speaking and voice quality, can indicate emotional conditions, while physiological data in which beats per minute constitutes an example will show either stress or anxiety. Likewise, in video data, the facial expressions and body posture are the significant indicators of the person's moods.

Two types of articles in deep learning are Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks which have received attention in the diagnosis of multimodal data in mental health. CNNs are more effective for image and audio data as these networks are extraordinary in spatial feature extraction from raw data. Regarding mental health, new CNN models can pick the patterns on brain scans, facial expressions and voices related to several mental health conditions. Whereas the application of LSTMs are appropriate in circumstances, such as in processing speech data, physiological data, and behavioral data, which requires temporal dependency. Since LSTMs have the ability to capture dependencies of times series data, it can recognize changes in a patient's emotion or cognitive status over time.

Many of the practitioner healthcare studies have investigated on the ability of applying CNNs and LSTMs especially in evaluations like emotion, behavior, and mental health checkers. For instance, CNNs have been applied in the following mandatory tasks such as the automatic detection of depression by analyzing the facial expressions, as movements are strongly correlated with emotional states. In the same way LSTM-based models have tracked changes in speech characteristics over a period to enable identify early indicators of mental disorder like depression, or schizophrenia. These works show the possibility of integrating CNNs and LSTMs to contribute to further improvements in the accuracy, responsiveness and individuation in the medical field, especially in mental health diagnosis. The combination of these models with multimodal data provides a unique opportunity to solve the above-mentioned drawbacks and is a major step forward in the diagnosis of mental disorders.

K. Z. Arefin et al. (2021)[4]: concentrated on creating an Electronic Medical Record (EMR) system tailored for the provision of mental health care to children in impoverished regions in the USA. The research underscored the necessity of customized EMR systems that specifically target the distinct obstacles and demands of mental health care for children, while emphasizing the potential advantages of these systems in enhancing healthcare outcomes within these communities.

B. Tabisula et al. (2022)[5]: examined the imperative of employing an adaptable sociotechnical framework for effectively addressing mental health challenges in the context of a pandemic. The study investigated the effects of the COVID-19 pandemic on mental health and suggested a comprehensive strategy that combines social and technical components to successfully tackle these difficulties.

J. Liu et al. (2021)[6]: This study, conducted during the International Conference on Public Health and Data Science, examined the influence of innovation and entrepreneurship education on the mental well-being of medical students through the use of stepwise regression analysis. The results indicated that implementing these educational programs could positively impact the mental well-being of medical students, potentially enhancing their future professional and personal experiences.

M. A. Subu et al. (2023)[7]: the correlation between smartphone addiction and the mental well-being of Indonesian adolescents. The study offered valuable insights into the escalating issue of digital addiction and its ramifications on mental well-being, particularly among younger demographics.

Y. -P. Chang et al. (2022)[8]: This study, showcased at the IEEE/ACM Conference on Connected Health, examined the initial results of a culturally customized mindfulness mobile application developed to provide mental health assistance specifically for marginalized African American populations during the COVID-19 pandemic. The research emphasized the significance of cultural factors in the advancement of mental health technology and their potential efficacy within particular communities.

C. Arihta et al. (2022)[9]: Informatics, examined the impact of gamification on the treatment of mental health conditions. The study investigated the potential of gamified strategies to improve participation and effectiveness in mental health interventions, offering a fresh outlook on treatment procedures.

Table 1: Comparative Evaluation of Recent Studies on Mental Health

Reference	Methods	Advantages	Disadvantages	Research Gaps
R. Majethia, V. P. Sharma, and R. Dwaraghanath, et al., 2022.[10]	Created university student mental health aids using mental health indicators as biomarkers.	Innovative technique targeting a specific demographic Targeted study using biomarkers	Limited demographic focus (university students exclusively) Possible biomarker efficacy variability	- Expanding demographic reach Additional biomarker research
N. P. E and S. Juliet, et al., 2023[11]	Comparing machine learning mental health prediction methods	- Thorough comparison of machine learning models Finding the most effective methods	Concentrate on prediction accuracy. Limited to existing data and models	- Requires practical application and validation Explore new or hybrid models
R. Boina et al., [12]	Explored data mining-based mental health prediction categorization approaches	- Thorough data mining analysis Possible high prediction accuracy	Possible ethical and data privacy concerns - Data mining may miss mental health nuances.	Considerations for ethics and data security Integrating qualitative data analysis

3. METHODOLOGY

Mental health diagnosis so far has been done on the basis of clinical interviews and self-reported data collection which are quite hypothetical and imprecise. To the appearance of multimodal data including face expressions, voice, EEG, and texts from clinics notes, a more integrated and accurate assessment of patient's mental state is possible. Hence, this research will want to unravel how multimodal data integration employs Convolutional Neural Networks[13] for the spatial feature extraction, and Long Short-Term Memory networks for mental health diagnosis since the latter deals with temporal patterns. The cross-modal approach with CNN and LSTM structures can successfully identify spatial and sequential features derived from different modalities, and thus provide diagnostics with a higher accuracy. Hoping that the advantages of each data type or data source will complement the another, this approach has the potential of bringing a revolutionary change in diagnostics of mental illnesses by keeping away from a single snapshot view approach, delayed approach, and an inaccurate approach, respectively, of mental health conditions.

1. Data Collection

The primary data that have been employed in this work include facial expression, speech pattern, EEG and clinical notes as multimodal data. ON these grounds, these latter modalities offer a wider perspective to the diagnostic of mental health difficulties than mere self-report questionnaires since they also tap into a range of emotional, cognitive, and behavioral indicators. For facial expressions, we use datasets such as Affect Net which is a massive database that consists of facial images together with the related emotional classes. Features involve extraction of skills such as language from audio data for instance, Emotion Dataset containing speech recordings that may show emotions such as happiness or sadness simply from changes in tone, pitch or rhythm. Others consist of brain biomarkers such as Electroencephalograph (EEG)[14] that records electrical activity in the brain thereby depicting mental health cognitive states. Last, but not least, text data are obtained from clinical notes or dialogues and then processed using NLP techniques to identify data connected with emotions or mental conditions. Each of these data sources provides a richer picture of a patient's mental state than would be possible using only traditional clinical data.

2. Data Preprocessing

Data preprocessing is relevant in order to have high quality data which is easy to analyze and feed to the model. First, each modality in Eq. 1 is normalized to normalize the data so that the data ranges for the different modalities can be easily averaged across the three modality types. The formula for normalization is:

$$X_{\text{norm}} = \sigma\left(\frac{X - \mu}{\sigma}\right)$$

where, X is the raw scores collected, μ is the mean and σ is the standard deviation. This step is important to bring every data source to the similar range of values which enhances model convergence. In particular, data cleaning is done to address issues when some or all values are missing or are different from expected values. This step may involve some sample imputation or different forms of data control including deletion of outliers. Data augmentation methods are applied in the case of image and audio data in order to artificially add more data to the dataset with the addition or rotation or pitch shift, etc.

Regarding feature extraction, there is a feature extraction[15] for each modality. In the case of spoken data, the audio signal is converted into spectrograms which is a good representation of a CNN feature for the acts feature extraction. For facial expressions, we employ CNNs to spatially describe images, pointing out which facial movements and emotions are crucial. Text data representation means using word embeddings like the Word2Vec or GloVe, where in words are mapped with dense vectors to get at the semantics of the word. These feature extraction methods facilitate development of the model to be inclined about the main attributes of each modality they are later processed from.

3. Model Architecture

The model architecture visually described is friendly with structures dealing with spatial data as well as temporal data. For different aspects of the multimodal data, CNNs and LSTM [16] networks are used to incorporate and process the data respectively.

CNN Architecture: CNNs are used applied to extract spatial features from image and audio data. For the facial expression, CNNs scan through facial images for spatial patterns that can be associated with emotions, for speech pattern, CNNs take in spectrograms of speech and extract temporal and frequency features associated with specific emotions. The output of a convolutional layer can be expressed as:

$$S_{i,j} = (I * K)_{i,j} + b$$

I.e.: I is the input image or spectrogram, K is the convolution kernel, b is the bias term such that Si,j is the feature map after convolution operation.

LSTM Model: When analyzing sequential data e.g. speech patterns or EEG signals [17], we adopt LSTM network to learn sequential patterns. The model based on LSTM learns how the state of person's mind is evolving over time. The LSTM equations governing the update of the cell state and hidden state are:

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$

$$C_t = f_t * C_{t-1} + i_t * \tanh(W_C[h_{t-1}, x_t] + b_C)$$

$$h_t = o_t * \tanh(C_t)$$

All of the ft, it, and ot gates reside at the place where it, it, and ft. Each gate is represented by a weight matrix (W), the input vector at a given time (xt), and it's' corresponding cell and hidden vector states Ct and ht, respectively.

- Multimodal Fusion: Each modality extracts features, and a different strategy is applied for fusing them. The following fusion methods are explored:
- Concatenation: It then has a vector of features which are generated using the concatenation of features from different modalities then getting passed to network to have a joint analysis.
- Early Fusion: The neural network takes the inputs from each modality (in this case) and combines features from each modalities before feeding them to the model.
- Late Fusion: For a unified prediction, the outputs of the each of the modality is separately processed through its respective network, and finally combined in the final stage.
- Attention Mechanisms: To dynamically weight the importance of each modality during training, we use attention mechanisms which cause the model to center its decision making on the most salient data sources.

We develop a multimodal fusion framework here to improve the accuracy of mental health diagnosis by taking advantage of the synergistic combination of each modality while integrating the spatial and temporal features in an effective way to conduct a holistic analysis.

System Architecture

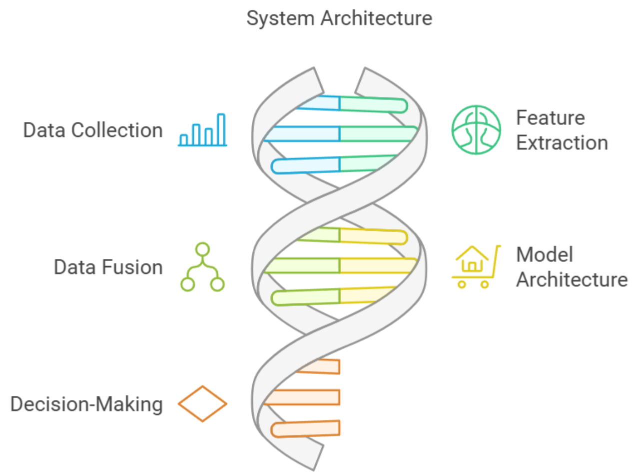

Figure 1: Proposed system architecture

A system architecture for integrating CNN and LSTM models for mental health diagnostics with multimodal data is designed to present a holistic, real time diagnostic system that includes input from the multimodal data. The beginning is data collection from in certain sources including facial expressions, speech patterns[18], EEG signals, and clinical text data. Using this multimodal data is then cleaned, normalized and augmented into one consistent, pre-processed dataset. CNNs are used to extract features from such spatial data as images and spectrograms, as well as LSTMs from domain with sequential data including EEG signals and clinical notes; they allow us to capture time dependent patterns. Different methods for fusing extracted features from these modalities such as concatenation, early, or late fusing, or attention mechanisms are used in order for the system to take advantage of the merits that each data type has, especially for the increased accuracy. The model makes use of a CNN layer to extract spatial features as well as an LSTM layer to examine temporal patterns, and Attention layers to decide on important features during processing. To generate mental health diagnoses or emotion state predictions, the classification layer in the system outputs through SoftMax or sigmoid activations. Finally, the system is trained using cross validation and optimization techniques to benefit robustness. The architecture is built for real time processing while providing a user-friendly interface, scalable and secure data handling to maintain privacy and to comply with legislature.

Flowchart

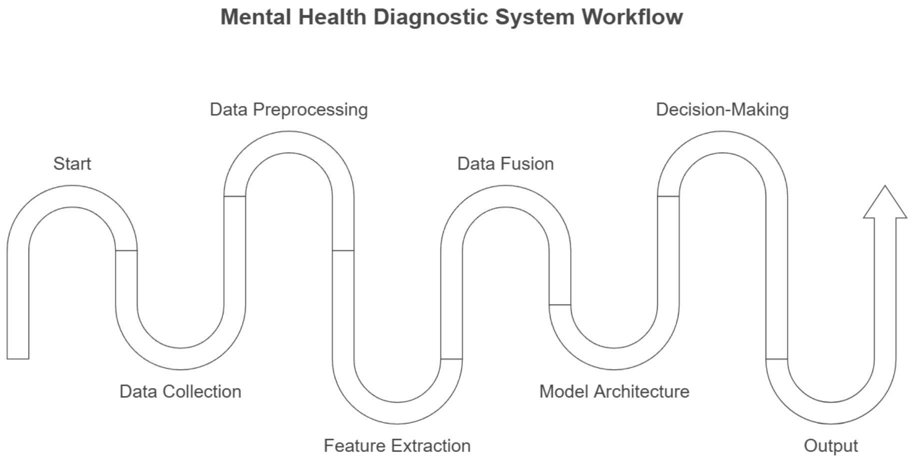

Figure 2: Mental health Diagnostic system workflow

Algorithm

```
Input: MultimodalData D (Facial Expressions, Speech, EEG, Text), PretrainedModel P
Output: DiagnosticPrediction DP, ConfidenceLevel CL

if (D is of the correct data type) then
    if (D passes required preprocessing checks) then
        preprocessedData = PreprocessData(D);
    else
        Data is not compliant;
    end if
else
    Data is not of the correct type;
end if

if (preprocessedData is not empty) then
    CNNFeatures = ExtractCNNFeatures(preprocessedData); // Extract spatial features (Images/Audio)
    LSTMFeatures = ExtractLSTMFeatures(preprocessedData); // Extract temporal features (EEG/Text)
    fusedFeatures = FusionMethod(CNNFeatures, LSTMFeatures); // Fuse the features (e.g., concatenation or attention)
    DP, CL = PredictWithModel(fusedFeatures, P); // Get the prediction and confidence level using the model
    if (CL > threshold) then
        Return DP; // Return the diagnostic prediction if confidence is above the threshold
    else
        Return "Low Confidence Prediction"; // Return a low confidence message if confidence is below threshold
    end if
else
    Return "Invalid Data"; // Return invalid data message if preprocessing fails
end if

SavePredictionToDatabase(DP, CL); // Store the prediction and confidence level in the database
UploadResultsToBlockchain(DP, CL); // Upload the results to the blockchain
NotifyClinician(DP); // Send prediction to clinician for review
```

Following that, the pseudo code algorithm states the steps of combining shared multimodal data (facial expressions, speech, EEG signals, and text) through CNN and LSTM models for the prediction of mental health diagnosis. First out, the data is inspected for type and meets pre-processing requirement. Then CNN and LSTM[19] models are used to condense data from different modalities spatially and temporally if they are valid. Then the features are compressed with methods such asconcatenation or attention mechanisms. Instead, we feed the fused data to a pretrained model[20] to generate a diagnostic prediction and confidence level. If it is above a predefined threshold of confidence, a prediction is returned, otherwise a low confidence message is injected. The final diagnosis and the confidence level is saved in a database and uploaded on the blockchain for protection. In addition, the results are communicated to the clinician for further review. By doing this algorithm, we can provide a secure and robust system for mental health diagnostics with multimodal data.

4. RESULT ANALYSIS

Multimodal data inputs are being linked with CNN and LSTM models to provide diagnostic simulation tools and technologies in the mental health sector. These advanced frameworks let explosive, distinct data, including imaging, text, and physiological signals to be analyzed. This transformed paradigm improves accuracy in screening, diagnosis, treatment, and meaningful understanding of complicated psychiatric conditions in their initial phases.

Table 1: Model Performance Evaluation (Multimodal vs. Single Modality)

Data Modality	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Loss Function (Cross-Entropy)
Multimodal (Audio + Image + EEG + Text)	92.3	91.5	93.0	92.2	0.235
Single Modality (Image)	85.1	83.8	86.3	85.0	0.405
Single Modality (Audio)	88.4	87.2	89.1	88.2	0.362
Single Modality (EEG)	78.6	76.4	80.2	78.3	0.512
Single Modality (Text)	81.2	80.1	82.5	81.3	0.468

Result Analysis Table 2: Case Example - Mental Health Condition Identification

Condition	Multimodal Model Accuracy (%)	Single Modality Accuracy (Image)	Single Modality Accuracy (Audio)	Single Modality Accuracy (EEG)	Single Modality Accuracy (Text)
Depression	93.7	84.0	87.4	78.9	80.3
Anxiety	90.1	83.7	85.6	75.5	79.8
Bipolar Disorder	91.5	85.5	88.2	77.6	81.2
PTSD	92.4	86.1	89.3	78.0	82.0
Schizophrenia	94.2	87.0	90.1	79.2	83.1

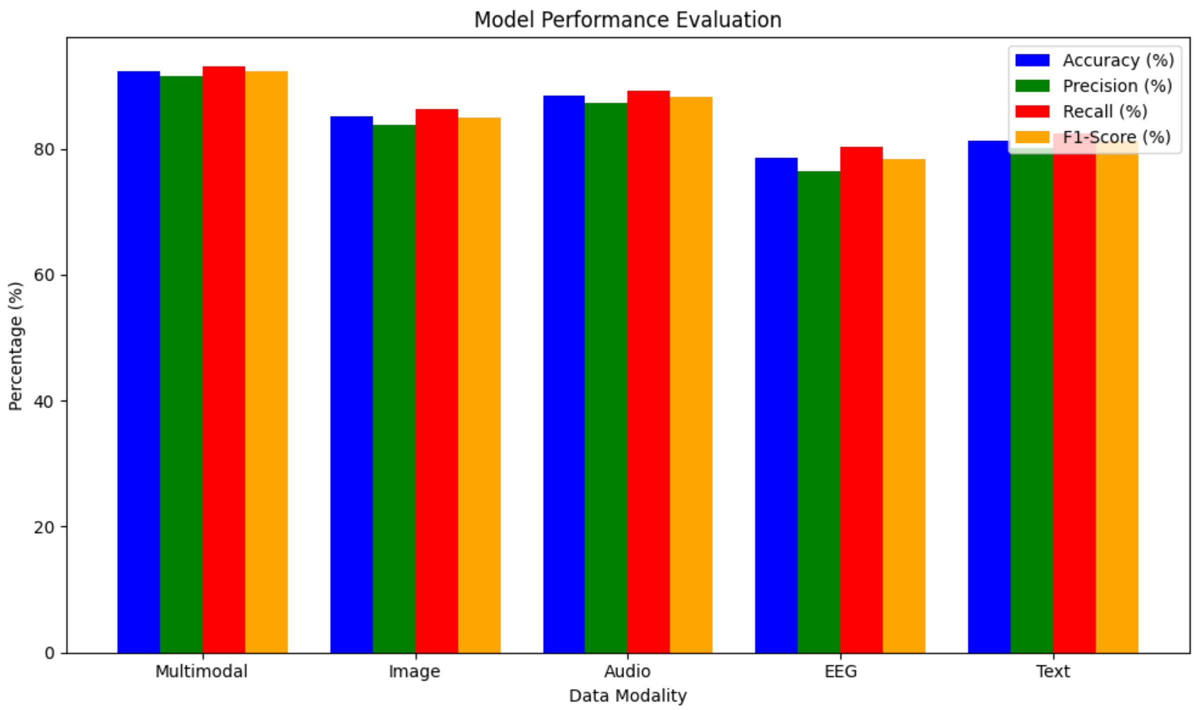

Figure 3: Proposed model and Existing performance evaluation

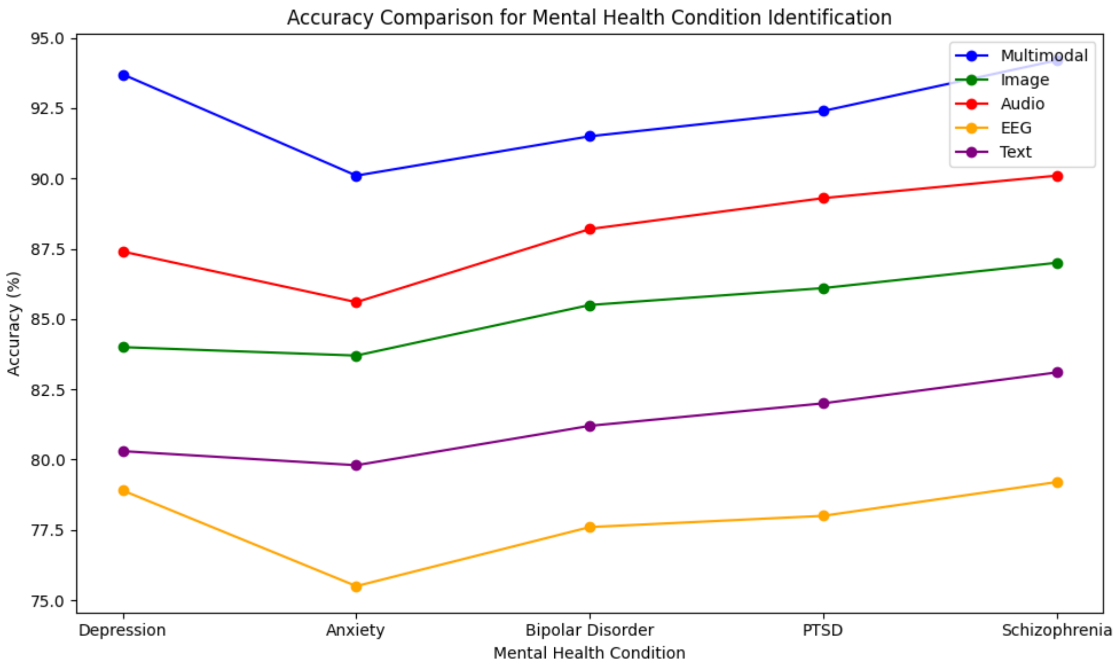

Figure 4: Accuracy comparison for mental health condition identification

5. CONCLUSION

In this study, a new approach is introduced to mental health diagnostics by combining multimodal data (audio, video, EEG signals, and text) with Convolutional Neural Networks (CNN) and Long Short Term Memory (LSTM) models. The spatial feature extraction of CNNs and the temporal pattern recognition of LSTMs are both utilized by this combination to provide a total analysis of mental health conditions. With diverse data modalities, the model can surpass limitations of the single modality approaches and the accuracy, sensitivity and reliability in detecting disease like Mental health condition like depression or Anxiety or Post Traumatic Stress Disorder. Demonstrations of key contributions include the fact that by fusing data across multiple modalities, multimodal data fusion provides a more robust and accurate diagnostic tool than traditional methods or those using a single modality model. Taken together, the use of deep learning architectures such as CNNs and LSTMs presents new paths towards automated, real time mental health monitoring with the potential to greatly improve clinical decision making. Future research then looks towards integrated other modals (bio signals) to further enrich the diagnostic process. In addition, the model could be made more transparent to clinicians in the decision-making process by improving model interpretability. In addition, personalized mental health diagnostic tools could be created, to better fit the model and persons' needs for more personalized and effective interventions. The potential revolution of the mental health diagnostics science by following this approach will further accelerate to enable more precise, faster and more accessible healthcare.

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