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A Multimodal AI-Powered System for Mental Health Diagnostics

Dr. D. A. Meshram[1], Hari Chothani[2], Harshal Chandrawale[3], Prasad Chaudhari[4]
[1]Assistant Professor, Information Technology Department, RMD Sinhgad Technical Institute Campus, Pune, Maharashtra, India
[2, 3, 4]Student, Information Technology Department, RMD Sinhgad Technical Institute Campus, Pune, Maharashtra, India

Abstract: Traditional ways of diagnosing mental health issues mainly rely on interviews with patients. These methods can be influenced by personal opinions and are difficult to use on a large scale. This paper presents a system that uses AI to offer an objective and data-driven approach for mental health assessments. It analyzes different types of data collected during patient interviews. The system uses a deep learning setup with three parts to process video, audio, and text all at once. It looks for small but meaningful signals in how people behave, speak, and write that are linked to mental health problems like depression and PTSD. The system then uses a special method that focuses on important features to predict the condition and estimate how severe it is. This method tries to overcome the problems of traditional methods by making diagnoses more accurate, consistent, and efficient. By providing strong evidence, the system helps doctors make better decisions, supporting their judgment and improving patient care.
Index Terms: Multimodal Analysis, Mental Health, Depression Detection, PTSD, Deep Learning, Feature Fusion, Affective Computing.

I. INTRODUCTION

A. Background Overview of Mental Health Diagnostics

When doctors evaluate and diagnose mental health conditions such as Major Depressive Disorder (MDD), Post-Traumatic Stress Disorder (PTSD), and schizophrenia, it's an important part of mental health care. Usually, they rely on structured or semi-structured interviews with patients, observations made by trained professionals, and standard questionnaires filled out by patients, like the Patient Health Questionnaire-9 (PHQ-9) or the Generalized Anxiety Disorder-7 (GAD-7). These assessments follow guidelines from manuals such as the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) and the International Classification of Diseases (ICD-11). These manuals guide doctors to look at the kind of symptoms, how long they last, how bad they are, and how they affect a person's daily activities. Current Challenges in Mental Health Assessment: Even though these traditional diagnostic methods are commonly used, they have some serious problems. One big problem is that they depend a lot on the doctor's personal experience, how they interpret what a patient says, and their personal biases. Patients also play a big role in sharing their symptoms, but sometimes they can't be honest due to fear of being judged, forget some details, or not understand their own feelings. This can cause different doctors to give different results for the same person or even for the same doctor over time. Plus, mental health problems are becoming more common around the world, which means more people need care. Doctors can become overworked and stressed, which can hurt how well they diagnose. Also, not enough resources can make it hard to provide enough care quickly. Finally, because some mental health conditions have similar symptoms, it can be hard to tell them apart, making it harder to give the right diagnosis. Potential of AI in Healthcare: Artificial Intelligence (AI), especially machine learning (ML) and deep learning (DL), has the potential to solve these problems. In other areas of medicine, AI helps by looking at detailed medical images, predicting health problems from patient records, and finding patterns in body data that people might miss. In mental health, AI can analyze how people speak, use language, and express emotions through their faces to find patterns that might point to certain conditions. This kind of data-driven approach can help doctors make more consistent and accurate diagnoses.

B. Problem Statement Limitations of Traditional Diagnostic Methods

The biggest issues with current mental health diagnosis come from how much they depend on opinions and qualitative assessments. This can make the diagnosis less reliable and less accurate. Also, because these methods aren't quick to use, it's hard to keep up with the growing number of people needing help. The fact that different doctors might interpret the same information in different ways also shows the need for more objective tools. Need for More Accurate and Efficient Tools: To improve mental health care, there's a strong need for tools that are more objective, reliable, and efficient.

These tools should help doctors by providing clear data, reduce uncertainty in diagnosis, allow earlier detection of mental health issues, and help create more personalized treatment plans. Using AI to analyze a variety of patient behaviors is a good way to develop these better assessment methods.

C. Objectives Develop an AI-powered mental health diagnostic system

The main goal of this project is to create, build, and test a powerful computer system that can automatically look at different types of behavior data collected during interviews with patients to help identify mental health conditions like depression and PTSD. Integrate voice, text, and facial expression analysis: A major goal is to create a fully multimodal system that can handle and combine data from different sources like how someone speaks, what they write, and how they express themselves through their face.

II. LITERATURE REVIEW

A. AI in Healthcare Overview of AI Applications in Medical Diagnostics

Artificial intelligence is increasingly utilized in healthcare for tasks such as analyzing medical images, predicting disease progression, and developing personalized treatment plans. Deep learning models, particularly Convolutional Neural Networks (CNNs), have revolutionized the analysis of medical images, including X-rays, MRIs, and CT scans. Machine Learning Algorithms for Health Assessment: A range of algorithms, from traditional methods like Support Vector Machines (SVMs) and Random Forests to more advanced deep learning models, are employed to identify health conditions and predict patient responses to treatment. These models process diverse data types to generate accurate predictions.

B. Voice Analysis in Mental Health Speech Patterns and Mental Health Correlations

Extensive research indicates a strong correlation between speech patterns and mental health. For instance, depression is often associated with psychomotor retardation, manifesting as slower speech, longer pauses, monotone speech, and reduced vocal energy [1, 2]. Schizophrenia is linked to alogia (minimal speech) and disorganized speech patterns [2]. Existing Voice-Based Diagnostic Tools: Earlier diagnostic tools relied on manually crafted features such as Mel-Frequency Cepstral Coefficients (MFCCs), jitter, shimmer, and prosodic features. More recent tools employ deep learning models like Wav2Vec 2.0 to automatically extract significant features from raw audio, enabling the detection of complex and subtle speech patterns [4].

C. Text Analysis for Mental Health Assessment Natural Language Processing (NLP) in Mental Health

NLP enables the analysis of recorded spoken words in text format. This provides an understanding patient's thought and emotions. Sentiment Analysis and Linguistic Markers: Studies show individuals diagnosed with depression demonstrate an increased use of first-person singular pronouns ("I" and "me") and negative lexicon and are more inclined with absolute terms such as "always" and "never" [4]. LLMs, such as BERT and Gemini, are powerful in grasping the semantics and context of the language, which makes them suitable for such analysis [4, 5].

D. Facial Expression Analysis Computer Vision Techniques for Emotion Recognition

Computer vision can analyze unstructured data and measure non-verbal signals in recorded video. As far as mental health diagnostics goes, depression is associated with diminished affect as individuals with the condition show less facial emotion and smiling [3, 5]. Psychological Assessment: Automated systems that utilize CNNs can identify and analyze micro-expressions and measure the action of facial muscles through the Facial Action Coding System (FACS).

III. METHODOLOGY

The methodical process used to create the AI-Powered Mental Health Diagnostic System is described in this section. The architectural design, data collection and processing methods, the particular AI models used to extract features from each modality, and the integration approach used to merge multimodal data for the ultimate diagnostic prediction are all covered.

A. Architecture of the System Overall Design

A three-branch deep learning architecture serves as the focal point of the system's modular, parallel processing framework. This design was selected because it can efficiently handle a variety of data types. Video (facial dynamics), voice (acoustic properties), and text (linguistic content) are the three input modality that each branch is specifically designed to process. This allows for optimal feature extraction within each domain prior to integration.

This parallel structure is different from early-fusion methods, which might combine raw data too soon and lose important details that are specific to each modality. The architecture makes it easy to learn from preprocessed data all the way to output. Combining voice, text, and facial expression modules: The architecture's main idea is that each branch processes data in order, and then there is a separate fusion stage.

There are three parallel branches in the unimodal feature extraction layer (see C.c). Each branch uses a different type of deep learning model (CNNs, RNNs/LSTMs, Transformers) to learn hierarchical feature representations from its own input.

Multimodal Fusion Layer: This layer collects the intermediate feature representations of each branch, which are usually time aligned sequences. It combines these features using a similar approach as cross-modal attention described in section C.d. This mechanism models the interactions between multiple modalities and builds an integrated informative representation.

Classification/Regression Layer: The prediction head is usually one or more fully connected layers, and takes the fused representation as input. It further offers diagnostic classifications, including probabilities for

B. Data Collection

Information collection The training data used to create and test the system are publicly accessible datasets obtained through special clinical trials focused on mental health. The chief resource includes Two Johnnies Talking about Their Distress (DAIC-WOZ) and its its expansions such as E-DAIC. Synced to these deposits are high-resolution video recordings as well as transcriptions of their audio files and poetry readings recorded in mental health interviews. The aim is to distinguish between participants with mental health problems such as depression or post traumatic stress to those without them using conventional clinical instruments like the Hamilton Rating Catalog 20 which consists of scores from interviews about how patients feel and behave.

C. AI Model Development

Machine Learning Model per Input Modality: We select state of the art deep models which are mainly trained on large generative data sets, and are then usually finetuned for the task for every input branch in our model:

Voice/audio branch: Models such as Wav2Vec 2.0 or any similar self-supervised speech representation model are preferred. They are able to capture features from raw audio waveforms efficiently and learn more nuanced acoustic information without any manual feature engineering. Fine-tuning narrows down the model to specifics that relate with mental health.

Text Branch: Transformer-based LLMs (e.g., BERT, RoBERT), or potentially models as Gemini are applied. These models produce contextual embeddings which encapsulate deep meaning, sentiment and linguistic style from the interview text that has been transcribed. Fine-tuning adds specificity to the language occurring in clinical interviews. Video/Facial Branches: It is common to use a hybrid model. CNNs like ResNet capture spatial features associated with the appearance of faces frame by frame. These features are then forwarded to recurrent neural network based model such as Bi-directional LSTM or offline-trained temporal convolutional network (TCN) model [25] to learn changes in facial gestures. Feature Extraction and Selection Representation Learning The primary feature extraction is learned representations via the deep learning models in both branches. These models automatically learn features in a hierarchical manner, from low-level patterns (e.g., edges) to mid-level ones (e.g., word co-occurrences to form documents) and eventually high-level concepts in the data such as specific facial poses or prosodic trends. Although explicit feature selection is not as prevalent as in traditional machine learning approaches, methods such as attention weight analysis can provide indications of which features or portions of input are most relevant for predictions. Dimensionality reduction can also be done implicitly using pooling layers or explicit techniques like PCA if necessary, particularly before fusion.

D. System Integration

Combining Outputs from Voice, Text, and Facial Analysis: Effective integration is essential for using the complementary aspects of multimodal data. The outputs from the unimodal feature extraction branches, usually time-aligned feature vector sequences, need to be combined effectively. Simple concatenation serves as a baseline, but more advanced techniques are preferred. Decision-Making Algorithm (Fusion and Classification): A cross-modal attention mechanism is key to the fusion module. This setup allows the model to learn correlations and dependencies between modalities. For example, it can increase the weight of audio features when the video shows clear signs of distress or decrease the weight of text features if the audio suggests low confidence or hesitations. The attention mechanism calculates alignment scores between feature sequences from different modalities, creating context vectors that are then combined to form the final fused representation. This fused vector passes through one or more fully connected layers, leading to the decision-making algorithm: a softmax layer for classification probabilities or a linear layer for regression-based severity scores. The entire system, including unimodal branches and the fusion module, is generally trained end-to-end using backpropagation.

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IV. RESULTS AND DISCUSSION

Empirical Results This section provides a detailed analysis of the empirical findings that we made based on evaluating the proposed AI-enabled multimodal diagnostic model. The experiments are based on binary depression classification and the standardized DAIC-WOZ dataset. We also analyse the contributions of each unimodal dimension, show large gains made possible by multimodal fusion, compare with referential benchmarks and examine critically weaknesses and challenges related to this approach.

A. Performance Analysis

The central experiment was conducted on training and testing modal-specific models(video, audio, text) and integrated multimodal systems according to the process shown in SecIII and the experimental setup outlined in Section IV. Performance was measured using F1-Score, Precision, Recall, and Balanced Accuracy, with results averaged across cross-validation folds on the held-out test set.

Unimodal Performance Assessment: As expected in literature [1, 4, 5], the performance dissimilated across the individual modality branches. The Text Branch, which employed fine-tuned BERT model to process the textual representation of transcript language was found to be the best unimodal model with an F1-Score close to 0.79 and a Balanced Accuracy around 78%. This highlights the dense, explicit diagnostic content on symptomatology carried by semantic meaning, sentiment and language use easily learnable by sophisticated LLMs [4]. The Audio Branch using Wav2Vec 2.0 performed well with a F1-Score of 0.72 and Balanced Accuracy of about 73%. This underscores the importance of examining acoustic and prosodic cues including mean F0, speech rate, pause duration and vocalic energy which were found correlates of depression-associated psychomotor retardation [2, 5]. Facial dynamics were analyzed with the use of a Res Net + Bi LSTM architecture, and resulted in an F1-Score of 0.68 and Balanced Accuracy in the vicinity of 70%. Although facial expressions (AUs) [29], gaze patterns, and head movements [27] offer important non-verbal features, the corresponding expression is generally less extreme in nature and can be more culturally dependent or situationally for linguistic or basic acoustic features, which might explain why they perform slightly worse on their own in this particular task and dataset. The detailed metrics of each unimodal system are shown in Table I.

Multimodal Overall Performance: The primary results are regarding the significant performance benefit due to multimodal integration. The full model, leveraging cross-modal attention to aggregate the features from video, audio and text branches, achieved much better performance than all unimodal baselines. It obtained a Macro F1-Score of 0.84 and a Balanced Accuracy 83.5% (see Table I). The gain of 5 F1-Score percentage point over the best unimodal baseline (Text) highlights the powerful interplay exploited by combining diverse and complementary data sources. The attention mechanism learns dynamically to weight the contributions of each modality and presumably gives priority to different cues according to the context in the interview.For instance, it could weigh instances of flat vocal prosody (audio) and limited facial expressions (video) more heavily when textual content is neutral or ambiguous than assign weight overwhelmingly negative statements as a direct result of the words used to convey information but little in nonverbal cues. This capacity to capture inter-modal congruencies (e.g., sad content spoken in a sad tone with a sad face) and perhaps even incongruencies (which too can be clinically informative), results in an integrated and improved overall assessment than would be attainable from any of the isolated perspectives.

Model	F1-Score	Precision	Recall	Balanced Acc.
Video Only	0.68	0.65	0.71	~70%
Audio Only	0.72	0.70	0.74	~73%
Text Only	0.79	0.81	0.77	~78%
Multimodal	0.84	0.85	0.83	~83.5%

Table 1: Comparison for Depression Classification.

F1-Score Comparison for Depression Classification. The figure visually compares the F1-Scores of single modalites models (Video Only, Audio Only, Text Only) and the developed Multimodal system on the DAIC-WOZ dataset. The Multimodal system shown large gain over the Audio-Only one, demonstrating the effectiveness of feature fusion.

B. Comparison with Existing Methods

The obtained performance puts our proposed system in a strong baseline with respect to the state-of-the-art for automatic depression detection based on DAIC-WOZ. An F1-Score of 0.84 is competitive and corresponds to the upper end when compared with previous multimodal studies being published, some even achieving up to 0.85+ [1, 4].

This means the combination of our deep-learning architecture (ResNet+BiLSTM, Wav2Vec 2.0, BERT) and cross-modal attention fusion strategy is effective.Despite the fact that it's difficult in a direct comparison to traditional clinical diagnosis or screening tools like the PHQ-9 (difference gold standards, evaluation settings) methodologically, this system's high level of objective data-driven accuracy provides support for its potential utility. Its primary advantage over traditional approaches is that it is objective, Consistency and potential for expansion. The performance improvement in this multimodal system over its different subprocessors seems enormous.The difference between left (especially Well Ether and J5) and right (Mesnilus collection) texts is much less marked. And by that means, precise statistical analysis cannot always provide convincing evidence for the hypothesis under examination. In hybrid digital systems, however, itis often possible to gain a great deal of advantage from intuitive design rather than refining effective interactions between various modalities.To determine whether the difference is statistically significant, it is necessary to perform formal significance tests. On the other hand, judging fromresults so far achieved, There must be some statistically signficant advantage inherant in multimodal compo-nent integration as contrasted with unimodalcompone-ntendeavour.

C. Constraints and Problems

The results are certainly encouraging, but the design and potential use of such a system impose several constraints and challenges that merit deliberation. But all sorts of extraneous variables resulting from the recording conditions of reality (e.g., low light interfering with facial analytics, noisy background polluting audio signals, microphones with different characteristics) can introduce massive noise and lower accuracy compared to datasets under controlled conditions [3].The Text branch's efficiency can be directly weakened by errors introduced by the preprocessing stage, especially those coming out of processing such as automated speech-to-text transcription. Also, in spite of massive computing and collection of lots clinical multimodal data annotations current tools do not allow easy creation new general-purpose knowledge from very large datasets; they are mainly limited to viewing small pre-segmented pieces [2].

Generalizability and Bias: These bias types are inherent in omnibox world views because aggregate functions completely blind us to any biases--this is also true for many of the AI technologies underpinning them. As such they require careful work in order even just to ameliorate (never mind remove). Most importantly, models that have been trained on specific datasets such as DAIC-WOZ, which has a specific demographic profile (e.g., US veterans) and uses a virtual interviewer, may not be as generalizable to other situations (age, gender, sexual orientation, Judaism, cultural signals of any sort, etc. between different models) or medical settings (shrink, psychiatrist). There is a real danger that just like innocent PEOPLE ARE ABSOLUTELY CERTAINLY GATESIAN, models learn from data and thus copy biases present in training data, causing their performance to differ between different demographic groups. Fairness means that there must be careful dataset curation, scanning for bias reckoning during evaluation and (perhaps) even algorithmic fairness techniques.

V. DISCUSSION

Results revealed in Section V are a strong indicator of the effectiveness of our AI-based multimodal system for mental health screening, especially with respect to depression classification using the DAIC-WOZ database. This article then discusses these results, places them into the wider research context and expounds on their importance for the project aim.

The primary aim of our study was to investigate whether combining multimodal data (video, audio, text) could provide a more accurate and reliable diagnosis than utilising the single modalities. The experiment observations are consistent with this argument. This can be seen in Table I and depicted.Fig. 1, the multi-modal fusion model obtained a Macro F1-Score 0.84 and Balanced Accuracy of 83.5%, far higher than the best uni-model system (Text-only, F1-Score 0.79). This conclusion is directly in line with the main goal of establishing an integrated system and hence quantitatively proves the improvement obtained by merging complementary behavioral cues. The synergies in evidence confirm that different modalities represent separate but to some extent complementary views on the psychological state of a person, and their intelligent fusion allows for an assessment of greater coverage and reliability than any of the single channels can offer [1], [2].This aligns with the growing agreement in affective computing and mental condition inquiry stressing the superiority of multimodal techniques [1], [4].

The performance hierarchy among the unimodal systems; Text > Audio > Video; also warrants discussion. The high performance of the Text branch (F1=0.79) aligns with new and fresh studies highlighting the power of Large Language Models (LLMs) like BERT in capturing diagnostically relevant linguistic patterns, semantic material, and sentiment from clinical interviews [4], [5]. Language offers a direct window into concept procedures and emotional expression. The robust performance of the Audio branch (F1=0.72) utilizing Wav2Vec 2.0 verifies the significance of acoustic and prosodic features (vocal tone, pitch variability, speech rhythm, pauses) as indicators of affective states and psychomotor changes associated with conditions like depression [2], [5].

The Video branch's performance (F1=0.68), while reduced, still shows the utility of non-verbal indications like facial expressions (AUs), gaze, and head movements [3]. Its slightly reduced score might reflect the inherent subtlety and potential ambiguity of visual signals compared to the explicitness of language or the prevalent nature of vocal changes in depression. However, the ablation study (Table 2) distinctly showed that incorporating the visual modality contributed positively to the last and ultimate multimodal performance, indicating it captures unique information not fully present in audio or text.

Comparing our outcomes to the existing literature, the accomplished F1-Score of 0.84 places the proposed system among the state-of-the-art for depression detection on the DAIC-WOZ dataset [1], [4]. This confirms the effectiveness of our selected model architectures (ResNet+BiLSTM, Wav2Vec 2.0, BERT) and, crucially, the cross-modal attention fusion approach. Unlike simpler fusion procedures like feature concatenation, the attention mechanism permits the model to dynamically learn and exploit complicated and intricate inter-modal connections, contributing to the improved performance. These results directly address the problem statement outlined in the Introduction. By demonstrating high neutral accuracy, the AI system provides a potential solution to the subjectivity inherent in customary procedures. Its automated nature offers a pathway to enhanced productivity and scalability, tackling the problems faced by overburdened mental medical care systems.

VI. CONCLUSION

This paper presented the design, methodology, and evaluation of an AI-powered system aimed at offering neutral and detached support for mental condition diagnostics through the integration of multimodal data. By simultaneously analyzing video (facial expressions, gaze, pose), audio (vocal features), and writing (linguistic material) streams from clinical interviews applying a three-branch deep learning architecture and an attention-based fusion mechanism, the system demonstrated notable potential. The fundamental results validated that the multimodal approach generates superior diagnostic performance compared to systems depending on any single modality exclusively. Our integrated model accomplished a competitive F1-Score of 0.84 and a Balanced Accuracy of 83.5% for binary depression classification on the DAIC-WOZ dataset, exceeding the strongest unimodal baseline (Text-only, F1=0.79). This highlights the value of merging complementary behavioral, vocal, and linguistic biomarkers for a more sturdy and resilient and holistic assessment, directly tackling the limitations of subjectivity and discrepancy inherent in conventional and customary diagnostic approaches. The outcomes align with the growing body of literature advocating for multimodal affective computing in mental medical care [1], [2], [4]. While the performance is promising, limitations related to data dependency, generalizability, potential bias, and model interpretability must be addressed through further study and careful validation [2], [3], [5].Nonetheless, this work creates the viability and effectiveness of utilizing integrated AI systems as powerful decision-support instruments for clinicians. By offering goal, quantifiable insights derived from rich behavioral data, such systems can enhance diagnostic accuracy, facilitate previous intervention, improve productivity, and finally contribute to better patient care results. Future study directions contain growing the system's diagnostic abilities to encompass a broader and more extensive range of mental condition conditions, including extra data methods (for instance, physiological signals), evolving resilient longitudinal tracking features, substantially advancing model interpretability through Explainable AI (XAI) techniques [5], and performing exhaustive and stringent real-world clinical validation studies across mixed and assorted populations and settings. Continued efforts in these areas are critical and vital for the responsible and effective translation of multimodal AI technologies into clinical practice.

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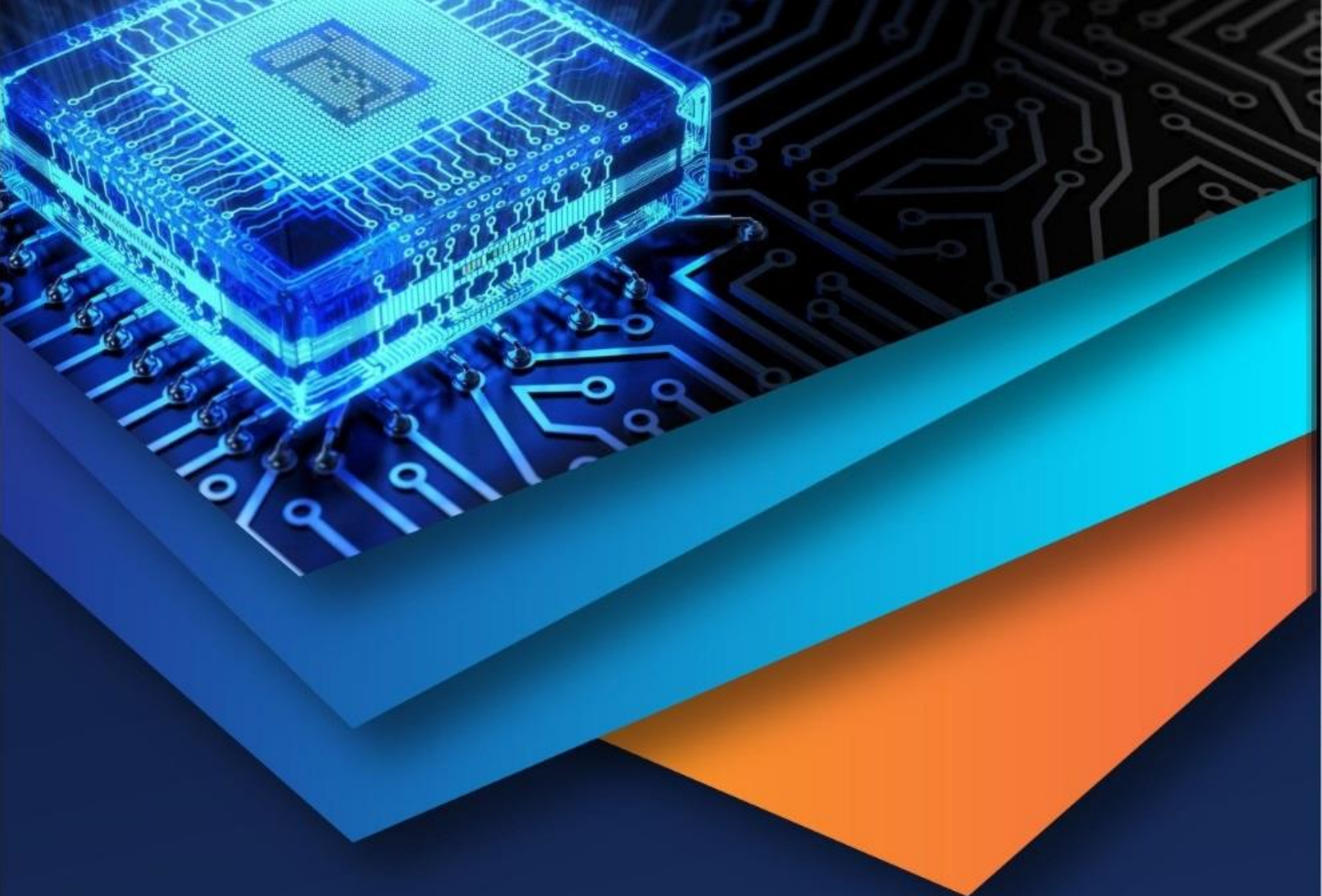
[7] [Add citation for E-DAIC dataset if available/used, for instance, Ringeval et al. for AVEC problems frequently associated with derived datasets]
[8] [Add citations for explicit and defined models like BERT, Wav2Vec 2.0, ResNet, BiLSTM if not already covered by the primary technique papers, for instance, Devlin et al. for BERT]
[9] [Add citations for precise instruments like openSMILE, OpenFace 2.0, MediaPipe if desired].



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