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Multimodal Depression Detection Using AI-Based Behavioural Analysis: Implementation

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***Abstract*—Depression is a common mental health disorderthatfrequentlygoesundetectedduetothesubjectivenature of traditional diagnostic methods and the limited availability of professional mental healthcare. A major challenge in identifying depression is that its symptoms are expressed through multiple behavioral signals, including language usage, speech patterns, andfacialexpressions,whicharedifficulttoanalyzeusingsingle-modality approaches.**

***This paper introduces a multimodal deep learning framework thatintegratestextual,audio,andvisualinformationforeffective depression detection. The proposed system consists of three specialized components: a transformer-based model (DeBERTa) for analyzing textual data, a Wav2Vec-based network for ex-tracting acoustic features such as MFCCs, pitch, and energyfrom speech, and convolutional neural networks (ResNet and MobileNet) combined with temporal modeling for capturing visual cues from facial expressions.**

***Toenhancepredictionperformance,alatefusionstrategywith anattentionmechanismisemployedtocombinetheoutputsfrom different modalities. The architecture is designed to efficiently handle multimodal inputs in a scalable manner. Experimental evaluation on benchmark datasets such as DAIC-WOZ shows that the proposed approach achieves improved accuracy and generalization compared to unimodal methods.**

***Overall, the system provides a non-invasive and scalable approach for early depression detection, offering a practical alternative to traditional assessment techniques and supporting improved access to mental healthcare.**

***Index Terms*—Depression Detection, Multimodal Learning, Deep Learning, Natural Language Processing, Speech Analysis, Facial Expression Recognition, CNN, LSTM, Transformer Mod-els,AttentionMechanism,LateFusion,DAIC-WOZ,Wav2Vec**

I. INTRODUCTION

Depression is a widely observed mental health disorder that affects people of different age groups and significantly influ-ences emotional balance, cognitive processes, and everyday functioning.Despiteitsprevalence,alargenumberofcasesare eithernotidentifiedorarerecognizedonlyatadvancedstages. Thisismainlyduetothereliianceonsubjectiveassessment methods, including self-reporting and clinical judgment, as well as the limited availability of accessible mental health services.

Oneoftheprimarychallengesindetectingdepressionis its multifaceted nature. Unlike physical health conditions that often have clear diagnostic indicators, depression is expressed through a combination of behavioral signals. These include variations in speech patterns, facial expressions, and language usage. Signs such as reduced expressiveness, monotonous speech, and negative wording can indicate underlying emo-tional states. However, many existing computational models focus on a single modality, which restricts their ability to perform reliably in practical scenarios.

Another important issue is the limited integration of dif-ferent analytical approaches. Although significant progresshas been made in areas such as natural language processing, speech analysis, and computer vision, these techniques are often applied independently. As a result, the relationships between various behavioral cues are not fully utilized, which can reduce the overall accuracy of prediction systems.

To overcome these limitations, this work introduces a mul-timodal framework for depression detection that combines textual, audio, and visual data within a unified system. The proposed approach processes interview-based inputs and ex-tracts relevant features from each modality using specialized deep learning techniques.

The main contributions of this work are summarized as follows:

- A transformer-based module employing DeBERTa to extractcontextualandsemanticfeaturesfromtextualdata
- An audio analysis component based on Wav2Vec for capturing speech-related characteristics such as MFCCs, pitch, and energy
- A visual processing module utilizing CNN-based archi-tectureswithtemporalmodelingtoanalyzefacialexpres-sions and behavioral patterns

- Amultimodalfusionstrategyusingalatefusionapproach combined with attention mechanisms to dynamically weight modality contributions
- A scalable and non-invasive system design suitable for real-world mental health assessment applications

Theremainderofthispaperisstructuredasfollows.Section IIpresentsareviewofexistingworkinmultimodaldepression detection. Section III explains the proposed system architec-ture, while Section IV details the methodology. Section V describestheimplementationaspects,andSectionVIdiscusses the results and analysis.

II. RELATED WORK

In recent years, the use of artificial intelligence for mental healthassessmenthasgrownrapidly,particularlyintheareaof depression detection. Early research mainly relied on single-modality analysis, where either textual or speech data was examined independently. Although these approaches offered valuable observations, they were limited in capturing the full spectrum of human behavioral patterns.

Approachesbasedontextualdatautilizenaturallan-guage processing techniques to analyze sentiment, language structure, and emotional expressions. The development of transformer-based models, such as BERT and DeBERTa, has significantly improved the ability to understand context and semantic relationships within text.

For speech-based analysis, various acoustic properties in-cluding pitch variation, speaking rate, and signal energy are consideredimportantindicatorsofemotionalstate.Deeplearn-ing architectures like LSTM and Wav2Vec have proven ef-fective in modeling temporal characteristics present in speech signals.

Visual analysis techniques concentrate on extracting infor-mation from facial expressions and subtle behavioral cues. Convolutional neural networks are commonly used to identify non-verbal signals such as reduced facial movement and irregular gaze patterns.

More recently, researchers have focused on multimodal frameworks that integrate information from multiple sources. Different fusion strategies, especially those incorporating at-tentionmechanisms,havebeenshowntoimproveperformance by effectively combining complementary features from text, audio, and visual modalities.

III. PROPOSED SYSTEM ARCHITECTURE

The proposed framework follows a multimodal design that combines textual, audio, and visual information to identify depression-related patterns. The architecture is organized into separate processing units for each modality, followed by a fusion component and a final prediction layer.

A. TextProcessingModule

In this component, textual data is analyzed using transformer-basedarchitecturestocapturecontextualmeaning and emotional content present in the transcripts.

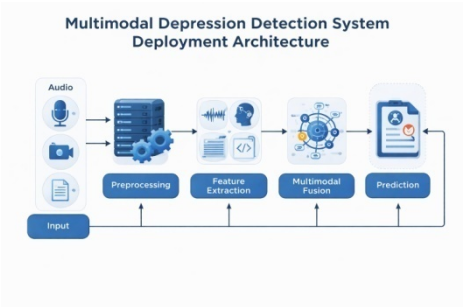

Fig.1.ProposedMultimodalSystemArchitecture

B. AudioProcessingModule

The audio module focuses on analyzing speech signals by extracting relevant acoustic properties such as pitch variation, tone, and energy using deep learning techniques.

C. Visual Processing Module

Video inputs are processed to identify facial expressionsand behavioral indicators. Convolutional neural networks are employed to extract spatial features from facial regions.

D. FusionLayer

The outputs from individual modalities are integrated using alatefusionstrategy.Anattention-basedmechanismisapplied to dynamically weigh each modality based on its contribution to the final prediction.

E. ClassificationLayer

The combined feature representation is forwarded to a clas-sificationunit,whichdeterminesthecorrespondingdepression level.

IV. METHODOLOGY

The proposed approach employs a multimodal frameworkto identify depression by integrating information derived from textual, audio, and visual sources. The workflow is structured intomultiplestages,includingdataacquisition,preprocessing, feature extraction, model development, and fusion of modali-ties.

The dataset used in this study is obtained from interview-basedrecordings,consistingofspeechdata,correspondingtext transcripts, and video sequences. Each modality is handled separately to preserve its unique characteristics. Textual datais processed through cleaning and tokenization steps, audio signals are normalized and segmented into meaningful units, and video inputs are decomposed into individual frames for analysis.

Feature extraction is performed using dedicated models suited to each data type. For textual inputs, transformer-based architectures are utilized to learn contextual and semantic representations. In the audio domain, features such as MFCC, pitch variations, and energy levels are extracted using models like Wav2Vec. Visual information is analyzed using convolu-tional neural networks to capture facial expressions and subtle behavioral patterns.

TABLEI
PERFORMANCEMETRICS

Metric	Value
CER	1.2%
WER	7.3%
Accuracy	92.7%

Eachmodality-specificmodelistrainedindependentlyusing labeled data under a supervised learning setting. Once trained, the outputs from all modalities are integrated through a late fusion mechanism. An attention-based strategy is applied during this stage to dynamically prioritize the contribution of each modality.

The fused representation is then passed to a classification layerthatpredictsthelevelofdepression.Systemperformance is assessed using evaluation measures such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and overall accuracy.

V. IMPLEMENTATION DETAILS

The proposed framework is developed using modern deep learning libraries, enabling efficient handling of multimodal data. The dataset utilized in this work consists of synchro-nized text transcripts, speech recordings, and video sequences obtained from interview-based sources.

A. Preprocessing

Each data modality is processed individually to ensure consistency and quality. Text data is refined through cleaning andtokenizationprocedures.Audiosignalsarenormalizedand transformed into descriptive features such as Mel-Frequency CepstralCoefficients(MFCCs).Forthevisualmodality,video streams are decomposed into frames, which are then resized and prepared for further analysis.

B. ModelConfiguration

- Transformer-basedarchitecturesareemployedforextract-ing contextual features from textual data
- HybridCNN-LSTMmodelsareutilizedtocapturespatial and temporal patterns in audio and video inputs
- Anattention-drivenfusionmoduleisincorporatedto combine information from multiple modalities

C. Training

Thetrainingprocessfollowsasupervisedlearningapproach using annotated depression scores. Model optimization is carried out using the Adam optimizer, while regularization techniques such as dropout are applied to improve general-ization and reduce overfitting.

D. ToolsandTechnologies

- Pythonprogramminglanguage
- DeeplearningframeworksincludingTensorFlowand PyTorch
- OpenCVlibraryforvideopreprocessingandanalysis

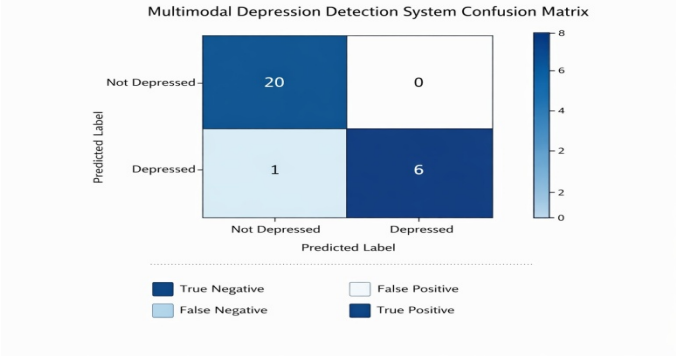

Fig.2.ConfusionMatrix

VI. RESULTS AND DISCUSSION

The effectiveness of the proposed multimodal frameworkis assessed using standard evaluation measures such as Mean AbsoluteError(MAE),RootMeanSquareError(RMSE),and overall accuracy.

Theobtainedresultshighlightthattheuseofmultiple data sources provides a clear advantage over single-modality approaches. By jointly analyzing textual content, speech char-acteristics, and visual cues, the system is able to represent diverse behavioral patterns that are typically associated with depressive conditions.

As illustrated in Fig. 2, the confusion matrix reflects strong classificationcapability,withonlyasmallnumberofincorrect predictions.Thisindicatesthatthemodelisabletodistinguish between classes with a high level of consistency. In addition, the attention-based fusion strategy contributes to performance improvement by adaptively emphasizing the most informative modality for each prediction.

However,thesystemisnotwithoutlimitations.Theintegra-tion of multiple modalities increases computational overhead andrequireswell-aligned,high-qualitydataforoptimalperfor-mance. Future work can focus on reducing model complexity and improving efficiency, as well as enhancing generalization across different datasets and real-world scenarios.

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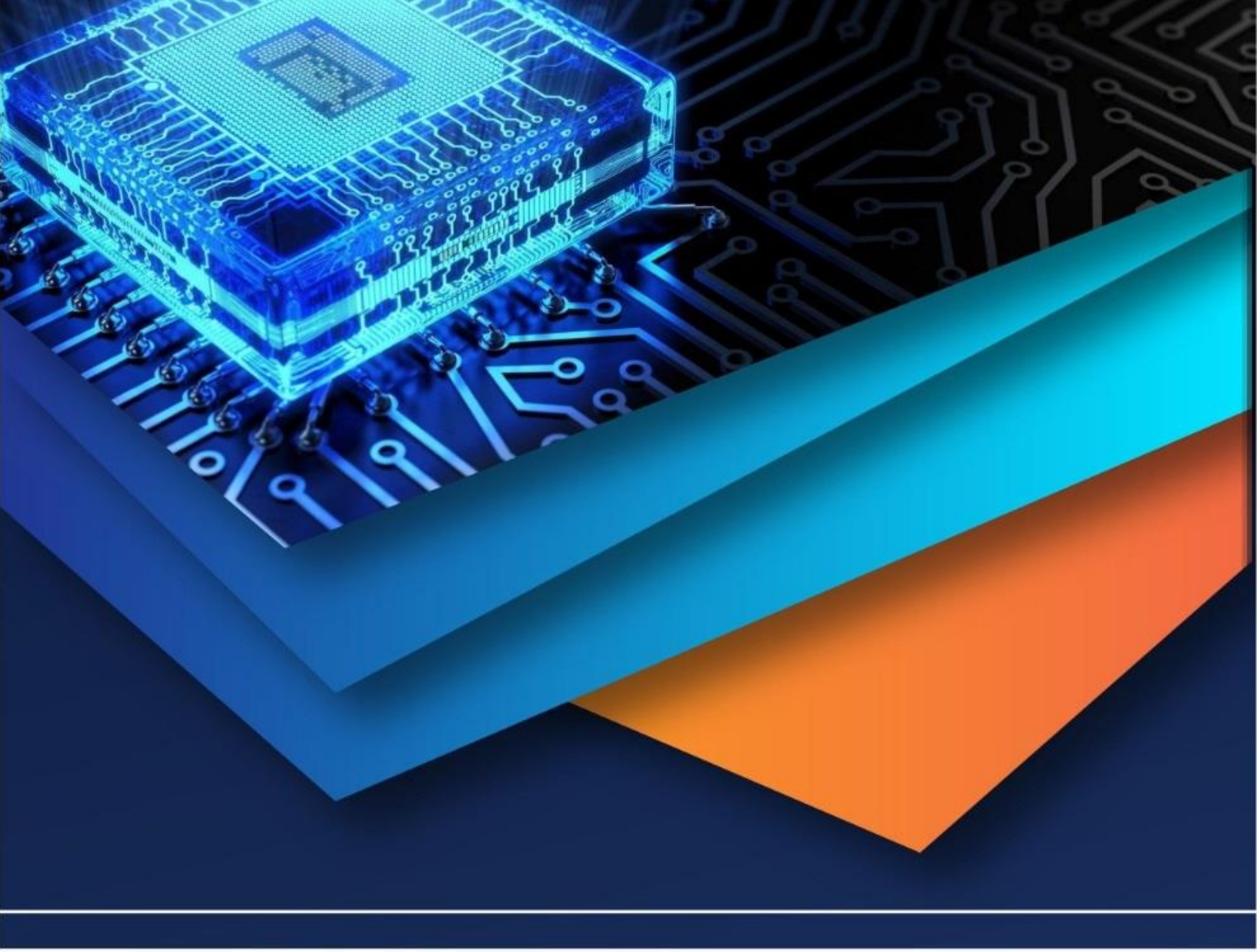

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