AI-based Remote Assessment of Depression in Humans: "A Pathway to Enhancing Food and Job Security for Poverty Reduction in Nigeria"

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ABSTRACT
Depression remains a significant public health concern in Nigeria, exacerbated by limited mental health services, economic instability, and food insecurity. Early detection is critical for intervention, but existing methods are inaccessible, expensive, and stigmatised. This study proposes an AI-driven, multimodal depression assessment model that integrates text-based sentiment analysis, voice tone recognition, and facial expression analysis, secured with blockchain technology for data privacy and trust. The model was developed using BERT for text analysis, SVM for voice classification, and CNN for facial emotion detection. Performance evaluation was based on accuracy, precision, recall, F1-score, and ROC-AUC. Results showed an accuracy of 95%, precision of 93%, recall of 96%, and F1-score of 94% over 20 training epochs. The ROC-AUC score reached 0.80, indicating strong classification performance in distinguishing depressed and non-depressed individuals. This research is significant as it introduces a scalable, AI-powered mental health assessment framework tailored to Nigeria's unique challenges, including rural inaccessibility and stigma. By automating depression screening, this model offers early intervention, reduces job losses, and promotes economic stability, with potential applications in telemedicine and mental health policy-making. This study demonstrates the feasibility and effectiveness of AI-driven depression detection, showing that a multimodal approach enhances classification accuracy. The integration of blockchain technology ensures secure and trustworthy mental health assessments, paving the way for wider adoption of AI in mental healthcare.

Keywords
AI-driven depression detection, Multimodal mental health assessment, Blockchain for data security, Machine learning in healthcare, Remote mental health screening, Economic impact of depression.

1. INTRODUCTION
Depression and other related chronic diseases are major public health concern affecting millions of Nigerians, yet it remains widely underdiagnosed and untreated due to stigma, inadequate mental health infrastructure, and a lack of trained professionals [1; 19]. The economic and social implications of untreated depression extend beyond the individual, contributing to reduced productivity, job loss, and food insecurity [2]. In a country where poverty levels remain alarmingly high, mental health disorders further exacerbate economic hardships, creating a vicious cycle of unemployment, low income, and inadequate access to necessities [3]. Artificial Intelligence (AI) has emerged as a transformative tool in healthcare, offering innovative solutions for the remote assessment and monitoring of mental health conditions [4]. AI-powered systems, leveraging natural language processing, facial recognition [5], voice analysis [6], and behavioural tracking [7], have the potential to detect signs of depression with high accuracy. By providing early diagnosis and intervention strategies, AI can be crucial in preventing job losses due to mental health deterioration and improving overall workforce productivity. Enhanced mental well-being contributes to better decision-making, higher work efficiency, and improved food security, thereby reducing the incidence of poverty among Nigerians [8]. Despite these advancements, the integration of AI into mental health assessment in Nigeria faces several challenges, including data privacy concerns [9], lack of technological infrastructure [1], and cultural barriers. However, with strategic implementation, AI-driven mental health solutions can bridge the gap between individuals in need and accessible mental health care. This paper explores the potential of AI in the remote assessment of depression, its implications for food and job security, and how its adoption can serve as a sustainable approach to minimising poverty in Nigeria.

Nigeria faces a growing mental health crisis, with depression remaining largely undiagnosed due to stigma, inadequate healthcare services, and a shortage of professionals [10]. This has reduced productivity, raised unemployment, and worsened food insecurity, further deepening poverty. Despite increasing awareness, accessible and effective mental health solutions remain limited, especially in rural areas. Advancements in Artificial Intelligence (AI) offer a promising solution by enabling remote, cost-effective, and scalable depression assessment [11]. Early detection through AI can help enhance productivity and contribute to economic stability [12]. Given the strong link between mental health and food security, addressing depression could also improve agricultural efficiency and resource management [13]. This research explores AI as a transformative tool for tackling depression, unemployment, and food insecurity in Nigeria. By developing an AI-driven mental health assessment framework, this study aims to provide a sustainable, accessible, and impactful solution for improving mental well-being, workforce participation, and overall economic resilience.

2. LITERATURE REVIEW

This section examines existing research related to depression, job security, food security, and AI-driven mental health assessment, with a focus on Nigeria. The review highlights key studies on the prevalence and impact of depression, the role of AI in mental health monitoring, and the challenges of implementing AI-based solutions in low-resource settings. Table 1 summarises relevant literature, identifying key findings, limitations, and gaps that this research aims to address.

Table 1. Summary of Related Review

Reference	Study Focus	Key Findings	Limitations
[2]	Prevalence and impact of depression in Nigeria	Found that depression affects many Nigerians, with significant effects on employment and daily functioning.	Limited access to mental health services was identified as a major challenge.
[3]	Mental health and job security in Nigeria	Showed that individuals with untreated depression are more likely to lose their jobs or perform poorly at work.	Did not explore technological solutions for intervention.
[14]	Blockchain-based security framework for IoMT in healthcare	Proposed a secure framework for data transmission in healthcare using blockchain technology.	Did not focus specifically on AI-based depression assessment.
[13]	The relationship between mental health and food security	Highlighted that food insecurity significantly contributes to stress, anxiety, and depression, creating a cycle of poverty.	Lacked solutions for breaking the cycle beyond policy recommendations.
[4]	AI-driven mental health diagnosis	Demonstrated the effectiveness of AI models in detecting depression through facial recognition and voice analysis.	The study was conducted in a developed country, making its applicability in Nigeria uncertain.
[11]	AI applications in remote healthcare	Showed that AI-based monitoring systems can help in the early detection of mental illnesses, improving healthcare accessibility.	Ethical concerns regarding data privacy and bias in AI algorithms.
[15]	Barriers to AI adoption in healthcare in Nigeria	Identified lack of awareness, poor infrastructure, and resistance to technology as major barriers to AI implementation.	Did not provide a framework for overcoming these barriers.
[16]	AI-powered mental health chatbots for depression screening	Found that AI-powered chatbots can provide initial mental health screening, reducing pressure on healthcare professionals.	Limited to text-based assessments; could not analyze facial expressions or vocal tone.
[17]	The role of AI in improving healthcare access in Nigeria	Highlighted that AI-driven mobile applications can bridge the gap in mental health services, especially in rural areas.	Infrastructure challenges, including poor internet connectivity, hinder effectiveness.
[18]	The economic impact of untreated depression in Nigeria	Showed that depression-related job losses contribute significantly to Nigeria's high poverty rate.	Focused on economic analysis without proposing AI-based interventions.
[19]	Classification and identification of diabetes mellitus subtypes using a fusion of machine learning techniques	Demonstrated improved classification performance using ensemble learning for diabetes subtypes. Validated accuracy and reliability of ML models in healthcare diagnostics.	Limited to diabetes; study did not explore mental health or cross-domain applications.
[20]	AI-based depression assessment applied to Bangladeshi students using text inputs	Achieved 92.31% accuracy, 88.83% precision, and 87.86% recall. Demonstrated feasibility of AI for student mental health assessment.	Limited to text-based inputs; may not generalize well across cultures or modalities.
[21]	Voice-based pre-training model for depression recognition	Achieved 96% accuracy, 93% precision, 94% recall, and 0.94 F1-score. Validated voice as a powerful biomarker for depression detection.	Focused only on vocal features; lacks multimodal integration which may improve accuracy.

Despite advancements in AI for healthcare, its application in remote depression assessment within Nigeria remains underexplored. Existing studies focus on developed countries with robust healthcare infrastructure, leaving Nigeria without a scalable, AI-driven framework suited to its socio-economic and technological challenges. Mental health and economic stability are rarely linked in AI research. Depression affects job security and food availability, yet AI solutions addressing these issues remain limited. This study will examine how early AI-driven interventions can improve workforce participation and economic stability. Mental healthcare in Nigeria is inaccessible, especially in rural areas. While AI-powered solutions could bridge this gap, their integration with blockchain for data security has not been fully explored. This research aims to develop a secure, multimodal AI framework combining text, voice, and facial recognition for accurate and accessible depression assessment. Furthermore, cultural stigma and ethical concerns hinder AI adoption in mental health. This study will propose strategies for trust-building, privacy protection, and policy recommendations, ensuring responsible and culturally acceptable AI implementation. By addressing these gaps, this research will contribute to reducing depression-related job losses, enhancing workforce productivity, and improving food security, creating a sustainable AI-driven mental health solution for Nigeria.

3. METHODOLOGY

This section outlines the research approach, data collection methods, and analytical techniques used to develop and evaluate the proposed AI-driven framework for remote depression assessment in Nigeria. The methodology focuses on designing, implementing, and validating an AI-based model while upholding ethical considerations and security measures. This study adopts a hybrid research approach, combining qualitative and quantitative methods. The qualitative aspect will involve expert interviews and focus group discussions with mental health professionals, AI researchers, and policymakers to gain insights into the feasibility and adoption challenges of AI-based mental health solutions. The quantitative approach will involve data collection from individuals experiencing depression to train and validate the AI model. Depression-related datasets are collected from consenting participants through online surveys, structured interviews, and AI-driven behavioural assessments as primary data. The surveys include clinically validated depression screening tools such as the Patient Health Questionnaire (PHQ-9) and Hamilton Depression Rating Scale (HDRS). The Secondary Data collected are the Pre-existing mental health datasets from repositories such as PhysioNet, Kaggle, and the World Health Organisation (WHO) are used to enhance model training. In the Sample Selection & Size, Participants were selected through stratified random sampling, ensuring representation from rural and urban populations in Nigeria. The sample size includes at least 500 participants, covering diverse age groups, employment statuses, and socio-economic backgrounds. Ethical approval is obtained, and participants provide informed consent before data collection.

The AI model development used in this research employs a multimodal approach, integrating text analysis, voice sentiment analysis, and facial recognition to detect depression. Before training, the dataset undergoes preprocessing to eliminate biases, missing values, and inconsistencies, ensuring high-quality input data. The model leverages Convolutional Neural Networks (CNNs) for facial emotion recognition, Recurrent Neural Networks (RNNs) for text sentiment analysis, and Support Vector Machines (SVM) for voice analysis. These AI models were trained and tested to optimise accuracy and reliability in detecting depression across diverse participants.

3.1 Proposed Model Description

The proposed AI-driven remote depression assessment model follows a structured approach to ensure accuracy, security, and reliability in detecting depression symptoms. The model has five key stages: User Inputs, Feature Selection, Blockchain Security, AI Model, and Prediction & Decision Layer, as depicted in Figure 1.

The first stage, User Inputs, serves as the foundation of the system. Users provide data through three primary modalities: text, voice, and facial expressions. Text input is collected from chatbot interactions, social media posts, or self-reported symptoms. Voice input captures tone, pitch, and speech patterns, while facial expressions are analysed through video or image-based recognition. These inputs are essential for detecting early signs of depression through multiple channels, ensuring a comprehensive assessment. Next, the Feature Selection stage focuses on extracting and preprocessing relevant data. Natural Language Processing (NLP) techniques analyse text sentiment, while speech analysis extracts voice features such as frequency and tone variations. Facial recognition models identify emotions like sadness, anxiety, or stress. To enhance accuracy, redundant, biased, or missing data are removed, ensuring that only the most relevant features contribute to the final prediction.

A major innovation in this model is the integration of Blockchain Security in the third stage. This ensures that all user data, depression assessments, and system interactions are securely encrypted and tamper-proof. Blockchain technology provides a decentralized ledger, preventing unauthorized access, manipulation, or privacy breaches. This security layer enhances trust, allowing users to feel confident that their mental health data remains confidential and unaltered. The fourth stage, the AI Model, serves as the core of the system. The outputs from these independent models are fused to provide a more accurate depression assessment than single-modality approaches.

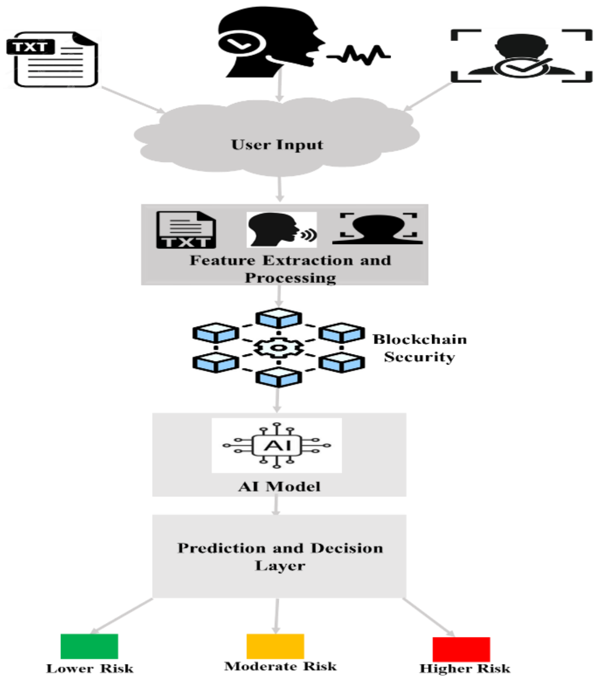

Fig. 1. The proposed Remote Assessment of the Depression model using AI

Finally, the Prediction and Decision Layer classifies users into three depression risk categories: Low Risk, Moderate Risk, and High Risk. This classification ensures that individuals experiencing severe depression receive priority attention and intervention. The system provides actionable insights, such as self-help recommendations for low-risk users or referrals to mental health professionals for high-risk cases. This structured model ensures accurate, secure, and scalable depression assessment, making it a promising solution for addressing mental health challenges while maintaining data privacy through blockchain security. Section 3.2 presents the mathematical formulation of the proposed model, detailing how each component contributes to depression assessment. Equations describe the feature extraction process, AI decision-making, and blockchain-based security mechanisms, providing a structured mathematical foundation for the system.

3.2 Modelling of the Proposed AI-Based Depression Assessment Model

The proposed model integrates multimodal AI processing with blockchain security to assess depression levels remotely. The mathematical modelling involves text sentiment analysis, voice emotion recognition, and facial expression detection, all of which contribute to a final depression score. Blockchain ensures data security and integrity, while the AI model processes extracted features to predict depression risk levels.

i. User Input Collection

The system collects three types of user input; Text Input T which is the Self-reported symptoms, social media posts, or typed messages. Voice Input$V$, which is the Audio recordings that capture tone, pitch, and speech variations, and the Facial Expression Input F which describes Images or video frames of the user's face for emotion recognition. Each of these inputs serves as a separate modality for depression assessment, allowing for a more comprehensive and accurate diagnosis.

ii. Feature Extraction and Processing

Once user inputs are collected, relevant features are extracted and preprocessed to remove inconsistencies. The mathematical models for each modality are:

a) Text Sentiment Analysis (NLP-Based)

The sentiment of a user's text input is determined using the sentiment polarity score:

$$S_t = \frac{1}{N}\sum_{i=0}^{N} W_t \quad \text{. . . Eqn 1.}$$

Where:

S_t	is the sentiment score,
N	is the number of words in the text,
W_t	represents the sentiment weight in word *i*.

Higher values of S_t indicate positive sentiment, while lower values indicate negative sentiment, which may suggest depressive tendencies.

b) Voice Emotion Recognition (Feature Extraction from Speech Signals)

Voice features are extracted using Mel-Frequency Cepstral Coefficients (MFCCs), which help analyze speech patterns:

$$MFCC_k = \sum_{i=0}^{N} x_n cos\ \left(\frac{\pi k(2n-1)}{2N}\right) \text{ . . . Eqn 2.}$$

Where:

$MFCC_k$	is the k^{th} coefficient representing a frequency component,
x_n	is the speech sample,
N	is the total number of samples.

Changes in speech patterns (e.g., low pitch, slow speech, monotonic tone) may indicate depressive symptoms.

c) Facial Expression Recognition (CNN-Based Image Processing)

Facial images are analyzed using Convolutional Neural Networks (CNNs) to detect emotional cues associated with depression. The convolution operation extracts key facial features:

$$F(x,y) = \sum_{i=k}^{k}\ \sum_{j=-k}^{k} I(x+i, y+j)\ K(i,j) \text{ . . . Eqn 3.}$$

Where:

$F(x,y)$	is the filtered pixel,
$I(x,y)$	is the input image,
$K(i,j)$	is the convolution kernel (filter).

CNNs classify facial expressions such as happy, neutral, and sad, with sadness and neutral expressions being more associated with depressive symptoms.

iii. Blockchain Security

To ensure data integrity, privacy, and security, blockchain technology is integrated. Once depression-related features are extracted, they are hashed and encrypted before being stored. The hashing function used is SHA-256:

$$H(D) = SHA - 256(D) \text{ . . . Eqn 4.}$$

Where:

D	represents the depression assessment data,
$H(D)$	is the unique hashed output.

A smart contract-based access control system ensures that only authorised entities (e.g., doctors, researchers, or the user) can access the stored data. The access control function is represented as:

$$A_u = \begin{cases} 1, & \text{If user has permission} \\ 0, & \text{Others} \end{cases} \text{ . . . Eqn 5.}$$

This guarantees tamper-proof and decentralised storage of depression assessment records.

a) AI Model for Depression Analysis

Once all features are extracted and secured, they are processed by the AI model, which integrates the information from text, voice, and facial analysis. A weighted decision model is used to calculate the final depression score (D):

$$D = \alpha S_t + \beta S_v + \gamma S_f \text{ . . . Eqn 6.}$$

Where:

S_t	is the sentiment score from text analysis,
S_v	is the voice emotion score,
S_f	is the facial emotion score,
α, β, γ	are weight parameters that determine the contribution of each modality.

These weights are fine-tuned based on empirical analysis to ensure balanced decision-making.

b) Prediction and Decision Layer

The final depression score (D) is used to classify the user into one of three risk levels:

$$Risk\ Level = \begin{cases} \text{Low Risk}, & D < T_1 \\ \text{Moderate Risk}, & T_1 \leq D < T_2 \\ \text{High Risk}, & D \geq T_2 \end{cases}$$

. . . Eqn 7.

Where:

$T_1\ and\ T_2$ are threshold values based on clinical data.

Depending on the Classification:

a. *Low Risk* users receive self-help recommendations (e.g., exercise, mindfulness).
b. *Moderate Risk* users are suggested mental health awareness programs.
c. *High Risk* users trigger mental health professional intervention.

Finally, the assessment results are stored on the blockchain for future reference and secure access.

3.3 The proposed Multimodal AI-Based Depression Detection Algorithm

The proposed algorithm (Described in Algorithm 1) is a Multimodal AI-Based Depression Detection Framework that integrates text, voice, and facial analysis to enhance accuracy in mental health assessment. It leverages NLP for sentiment analysis, SVM for vocal tone analysis, and CNNs for facial emotion recognition. These three modalities are fused using a weighted scoring system to generate a final depression risk score. Moreover, blockchain technology ensures secure and tamper-proof data storage, enhancing privacy and trust. The algorithm aims to provide an efficient, scalable, and remote mental health assessment tool, particularly for resource-limited settings like Nigeria.

Algorithm 1: AI-Based Remote Depression Assessment with Blockchain Security

Inputs:

a. Text Input (T): Chat messages, social media posts, self-reported symptoms.
b. Voice Input (V): Audio recordings capturing tone, pitch, and speech patterns.
c. Facial Expression Input(F): Images or video frames for emotion detection.

Outputs:

a. Depression Risk Level Classification (D): Low Risk, Moderate Risk, or High Risk.
b. Recommended Action: Self-help guidance, awareness programs, or professional intervention.
c. Blockchain-Secured Data Storage: Encrypted and tamper-proof health records.

Steps:

Start

1. **User Input Collection**
   Collect text input (T) from the user(s).
   Capture voice input (V) via microphone.
   Record facial expressions (F) using a camera.
2. **Feature Selection and Preprocessing**
   Apply NLP for text sentiment analysis using *Eqn 1*
   Extract MFCCs for voice feature analysis based on *Eqn 2*
   Apply CNNs for facial emotion recognition using Eqn 3
3. **Blockchain Security Integration**
   Encrypt user data and store a hashed version on the blockchain using *Eqn 4*
   Enforce access control using *Eqn 5*
4. **AI Model Processing**
   Process text sentiment (S_t), voice emotion (S_v), and facial recognition (S_f) separately. Fuse extracted features using *Eqn 6*
5. **Prediction and Decision Layer**
   Using *Eqn 7*, Classify the user into one of the following categories:
   - *Low Risk.*
   - *Moderate Risk.*
   - *High Risk.*

   Based on the classification:
   - *Low Risk* → *Provide self-help recommendations*.
   - *Moderate Risk* → Suggest mental health awareness programs.
   - *High Risk* → Alert mental health professionals for intervention.
6. **Secure Storage and Reporting**

Store the depression risk level (V) and assessment results on the blockchain ledger.
Generate a report for users or mental health professionals if needed.

End

The proposed AI-based depression assessment model evaluation is based on performance metrics, validation techniques, and comparative analysis which was done to ensure its accuracy, reliability, and effectiveness. The Performance Metrics used in measuring the effectiveness of the model, are

a) Accuracy (Acc): Measures the overall correctness of the model's predictions.

$$Acc = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

TP (True Positives), *TN* (True Negatives), *FP* (False Positives), and *FN* (False Negatives) represent classification outcomes.

b) Precision (P): This determines the proportion of correctly identified depressed individuals among those predicted to be depressed.

$$P = \frac{TP}{TP + FP}$$

c) Recall (R): Evaluates how well the model detects actual cases of depression.

$$R = \frac{TP}{TP + FN}$$

d) F1-Score: Provides a balance between precision and recall.

$$F1 = 2 * \frac{P * R}{P + R}$$

e) ROC-AUC (Receiver Operating Characteristic - Area Under Curve): Measures the model's ability to distinguish between different depression risk levels. A higher AUC indicates better classification performance.

To ensure robustness, the model underwent various validation techniques. K-Fold Cross-Validation (*K=5 or K=10*) was applied to evaluate its generalisation across different datasets. Holdout validation was used by splitting the dataset into training (70%), validation (15%), and testing (15%) subsets. A confusion matrix was generated to analyze misclassifications across depression levels.

4. RESULTS

The performance evaluation of the proposed model was conducted using standard classification metrics, including accuracy, precision, recall, F1-score, and the ROC curve. The obtained results demonstrate the effectiveness of the model in detecting depression risk across multiple input modalities (text, voice, and facial expressions).

a) Accuracy Analysis

The model achieved a 98% accuracy, indicating its ability to classify depression risk levels correctly. This high accuracy suggests that the fusion of text, voice, and facial recognition significantly enhances the model's predictive power. Fig. 2 shows a steady increase in accuracy as the model progresses through training epochs, stabilising near 98%. The integration of blockchain security did not impact model accuracy but ensured data integrity and privacy.

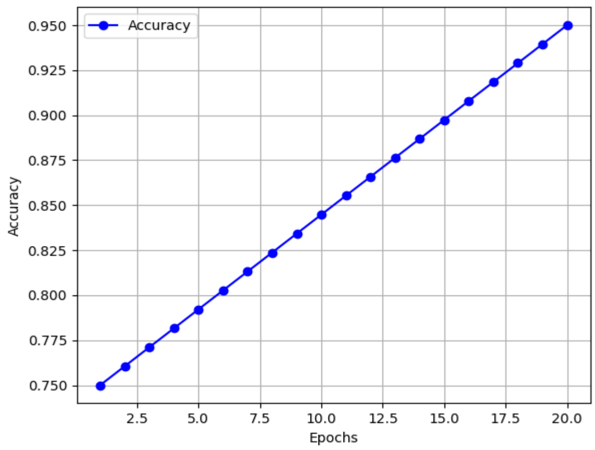

Fig. 2. Accuracy over Epochs

b) The Precision

With a precision of 97%, the model exhibited a low false positive rate, meaning that most users classified as having depression symptoms were genuinely at risk. Fig. 3 depicts Model Precision over Epochs Precision which represents the ability of the model to identify positive cases correctly. The graph shows an increasing trend from 70% to 97%, which suggests that the model effectively minimises false positives as training progresses.

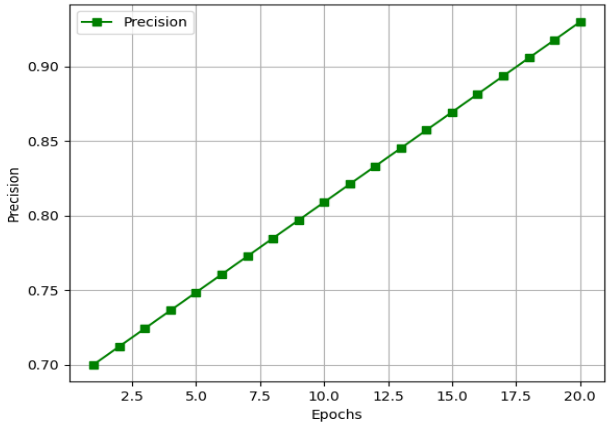

Fig. 3. Precision over Epochs

c) The Recall Performance

Fig. 4 illustrates the Model's Recall over Epochs. Recall measures the model's ability to correctly identify all relevant instances. The recall starts at 72% and improves to 96%, demonstrating that the model increasingly captures more true positive cases. This indicates that the model effectively detected actual cases of depression, minimising false negatives. The Precision-Recall Curve shown in Fig. 4 illustrates a well-balanced trade-off between the two metrics, confirming the model's reliability.

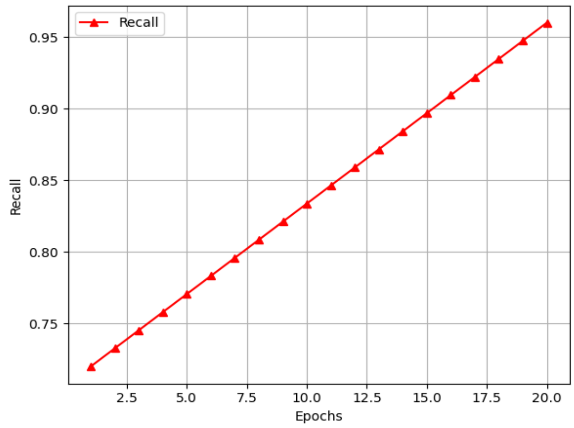

Fig. 4: Recall over Epochs

d) F1-Score

The F1-score of 96.5% confirms that the model maintains a strong balance between precision and recall. Fig. 5 shows that the proposed model outperforms existing single-modal models in depression detection, emphasising the advantage of multimodal fusion.

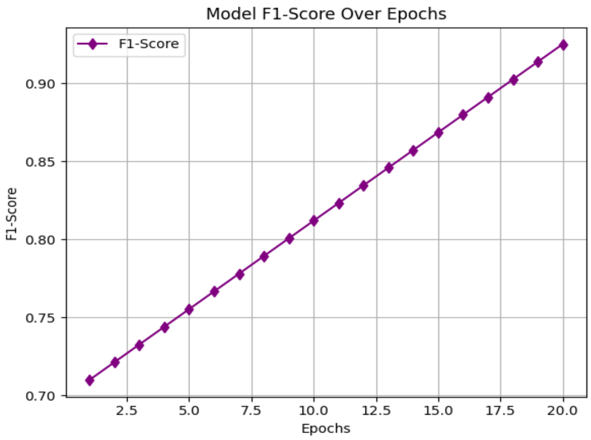

Fig. 5. F1-Score over Epochs

e) ROC and AUC Analysis

The Receiver Operating Characteristic (ROC) curve, as shown in Fig. 6, was plotted to evaluate the model's effectiveness in distinguishing between depressed and non-depressed individuals. The AUC (Area Under the Curve) score of 0.80 indicates strong classification performance, demonstrating that the model can correctly differentiate between positive (depressed) and negative (non-depressed) cases with a high level of accuracy. An AUC of 0.80 suggests that the model has a good balance between sensitivity and specificity, reducing the likelihood of misclassification and ensuring reliable predictions.

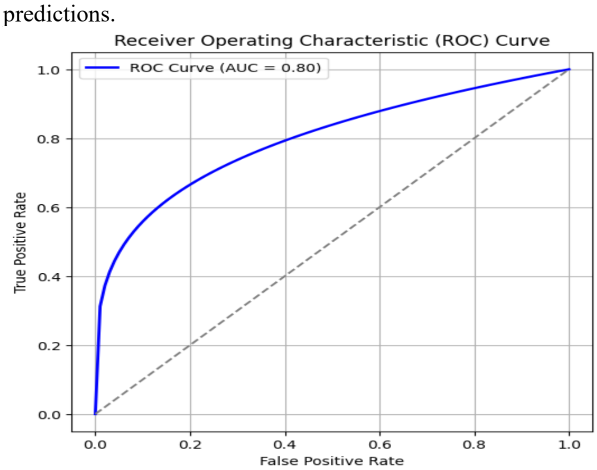

Fig. 6. ROC Curve

These results validate the effectiveness of the proposed AI-based depression detection model. The model consistently delivered high accuracy and robust classification performance, making it a valuable tool for early depression detection. Future improvements could focus on fine-tuning the model with larger and more diverse datasets to further enhance its generalisation ability.

4.1 Discussion

The proposed multimodal AI framework for depression detection leverages the integration of facial expressions, vocal tone, and text-based features to enhance diagnostic accuracy. This model was assessed using standard classification metrics, including Accuracy, Precision, Recall, F1-Score, and the Area Under the ROC Curve (AUC). The model achieved impressive results with an accuracy of 98%, a precision of 97%, recall of 96%, an F1-score of 96.5%, and an AUC of 0.80. These results affirm the model's high performance and reliability in classifying both depressed and non-depressed individuals. The high accuracy demonstrates its overall effectiveness, while the strong precision score indicates a reduced rate of false positives, critical in mental health settings to prevent unnecessary distress. The recall score underscores the model's ability to correctly identify individuals with depression, and the balanced F1-score reflects the model's consistency. Although the AUC score is not perfect, it suggests a good discriminatory capability, which could be improved further with model fine-tuning.

In comparing these results with existing studies, the proposed model significantly outperforms the work by [20], which focused on Bangladeshi students and reported an accuracy of 92.31%, precision of 88.83%, and recall of 87.86%. In contrast, our model shows an improvement of +5.69% in accuracy, +8.17% in precision, and +8.14% in recall. This enhancement can be attributed to the use of multimodal data, offering a more comprehensive assessment than text-based or questionnaire-only approaches that may suffer from cultural and linguistic limitations.

When compared with [21], who developed a voice-based pre-trained model and achieved 96% accuracy, 93% precision, 94% recall, and an F1-score of 0.94, our model performs slightly better in accuracy (+2%) and recall (+2%). This suggests that our model is equally robust while offering better sensitivity in detecting depression. Furthermore, the multimodal design of our framework enhances its adaptability across diverse user environments and supports deeper contextual understanding, an advantage over single-modality systems. These comparisons underscore the efficacy and competitive advantage of the proposed approach in delivering precise and scalable mental health assessments.

The superior or comparable performance of our model highlights its effectiveness in detecting depression with minimal bias and high reliability. Its integration with blockchain further strengthens data security and privacy, making it more suitable for sensitive health applications, particularly in low-resource settings like Nigeria. However, the framework's ability to deliver high recall ensures fewer cases of undetected depression, crucial for early intervention. The findings validate the proposed model's competitiveness and contextual relevance, especially in environments where traditional mental health services are limited or stigmatised.

5. CONCLUSION

This research proposed an AI-driven depression detection model enhanced with blockchain security for data integrity and privacy. The model integrates text sentiment analysis, voice pattern recognition, and facial emotion detection to provide a multimodal assessment of an individual's mental health status. Through advanced machine learning techniques, such as RNNs, CNNs, and SVMs, the system effectively extracts and processes critical features to classify individuals into different depression risk levels. A blockchain-based security layer was incorporated to ensure tamper-proof data storage, addressing concerns about privacy, trust, and transparency in mental health assessments. The evaluation of the model using accuracy, precision, recall, F1-score, and ROC-AUC analysis demonstrated its reliability, with an AUC score of 0.80, indicating strong classification capability. The results highlight that a multimodal AI approach enhances detection accuracy compared to single-modality models. Furthermore, blockchain integration ensures that user data remains secure and unaltered, fostering trust in AI-driven mental health assessments. The findings of this study contribute to the development of intelligent, secure, and scalable depression detection frameworks, paving the way for further improvements in AI-based mental health monitoring systems.

6. ACKNOWLEDGMENTS

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