ISSN: 2582 - 6379
IJISEA Publications
International Journal for Interdisciplinary Sciences and Engineering Applications
IJISEA - An International Peer- Reviewed Journal
2026, Volume 7 Issue 2
www.ijisea.org

Article Info

Date Received: 15/03/2026
Date Revised: 03/04/2026
Available Online: 22/04/2026

Identification of Psychological Stress from Speech Signal Using Deep Learning Algorithm

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10.5281/zenodo.19695480

ABSTRACT

Psychological stress has become a major issue in modern society due to increasing academic, social, and professional pressures, and early detection is critical to prevent serious mental health consequences. Existing systems predominantly rely on traditional assessment approaches such as surveys, questionnaires, and expert psychological evaluations, which are time-consuming, inherently subjective, and require trained clinical professionals. To overcome these limitations, this paper proposes an automated stress detection system built upon BERT (Bidirectional Encoder Representations from Transformers), a state-of-the-art deep learning model that analyzes user-generated text to classify whether content indicates stress or non-stress conditions. The system processes text through preprocessing, tokenization, and fine-tuned model training using Natural Language Processing (NLP) techniques. The technology stack includes Python, BERT, Deep Learning, NLP, PyTorch, the Transformers library, and Streamlit for a user-friendly web interface enabling real-time text analysis and probability visualization. Through optimized training strategies including stratified data splitting, learning rate scheduling, dropout regularization, and balanced datasets, the system achieves an accuracy exceeding 95%, making it a reliable and scalable tool for early psychological stress detection in educational, workplace, and healthcare environments.

Key words: Psychological Stress Detection, BERT, Deep Learning, NLP, Speech Signal Analysis, MFCCs, Text Classification, Mental Health Monitoring, Transformer Models, Streamlit, PyTorch, Real-Time Detection

1. INTRODUCTION

1.1 BRIEF INFORMATION

Mental health has emerged as a critical concern in modern society, with psychological stress affecting millions of individuals worldwide. The World Health Organization recognizes stress as a significant contributor to various physical and psychological disorders, including anxiety, depression, cardiovascular disease, and weakened immune function. Despite its prevalence and profound impact, early detection of psychological stress remains challenging due to the reliance on traditional assessment methods that are often subjective, require extensive clinical expertise, and depend on self-reported symptoms that individuals may be reluctant to disclose.

The advent of Artificial Intelligence (AI) and Natural Language Processing (NLP) presents unprecedented opportunities to revolutionize mental health assessment. Human communication, particularly written and spoken text, contains rich linguistic patterns and semantic cues that reflect underlying emotional and psychological states. People experiencing stress often exhibit distinctive language characteristics including negative sentiment, specific word choices, altered sentence structures, and particular emotional expressions that can be computationally analyzed with high accuracy [1].

This project addresses the critical need for automated, objective, and accessible psychological stress detection by leveraging state-of-the-art deep learning techniques. Specifically, we employ BERT (Bidirectional Encoder Representations from Transformers), a powerful transformer-based language model that has revolutionized natural language understanding tasks. By fine-tuning BERT on carefully curated stress-labeled text data, we develop a system capable of identifying psychological stress indicators with accuracy exceeding 95%, providing a scalable solution for mental health monitoring in educational institutions, workplaces, healthcare settings, and online platforms.

1.2 PURPOSE

The main purpose of this project is to develop an intelligent system that can automatically detect psychological stress by analyzing speech and text signals using deep learning techniques. The system studies variations in language patterns, tone, and semantic content to determine whether a person is experiencing stress. This approach enables early detection and supports mental health monitoring without the need for clinical intervention. The system is designed to:

- Early Stress Detection – Identify stress at an early stage before it escalates to severe conditions.
- Automated Analysis – Reduce the need for manual psychological evaluations using AI-driven classification.
- Deep Learning Accuracy – Leverage BERT and transformer models for improved accuracy in detecting stress patterns.
- Real-Time Applications – Enable deployment in healthcare systems, educational platforms, call centers, and mobile applications.
- Mental Health Support – Provide a non-invasive tool for monitoring emotional and psychological well-being.
- Improved Decision Making – Help professionals take early preventive actions based on automated predictions.

1.3 MOTIVATION

Psychological stress has become very common in modern life due to academic pressure, professional demands, and personal challenges. Many individuals experience stress but are unable to recognize or articulate it at an early stage. Traditional stress detection methods typically require questionnaires, medical tests, or expert evaluation, which can be time-consuming, costly, and subjective. This project is motivated by the need to develop an automated and efficient system that can detect psychological stress through natural language and speech signals [2].

Speech and text carry important emotional and psychological information such as tone, sentiment, and linguistic markers. Using deep learning algorithms like BERT, these patterns can be analyzed to identify stress levels accurately. The key motivating factors include:

- Increasing levels of mental stress in society due to academic and professional pressures.
- Lack of accessible, real-time tools for early psychological stress detection.
- Limitations of traditional manual stress assessment methods in terms of time, cost, and objectivity.
- Growing availability of pre-trained transformer models such as BERT that can be fine-tuned for specialized tasks.
- The potential for automated mental health monitoring in educational institutions, workplaces, and healthcare environments.

1.4 PROBLEM STATEMENT

Psychological stress has become a major concern in modern society due to increasing academic, professional, and personal pressures. Early identification of stress is essential to prevent serious mental health problems. However, traditional stress detection methods mainly depend on questionnaires, medical analysis, or expert observation, which are often time-consuming, subjective, and not suitable for real-time monitoring [3].

Text and speech signals contain valuable emotional and psychological information such as tone, pitch, and linguistic patterns. However, accurately identifying stress from these signals is challenging due to individual variation, linguistic diversity, and noise. The key problems identified are:

- Traditional stress detection methods are manual, time-consuming, and require clinical expertise.
- Subjective evaluation reduces consistency and reliability of results.
- Difficulty in achieving real-time, scalable stress monitoring.
- Absence of an integrated platform combining NLP, deep learning, and user-friendly visualization.
- Need for an automated system capable of analyzing large-scale speech or text data efficiently.

2. LITERATURE SURVEY

2.1 Introduction

Psychological stress detection has attracted significant research interest across the fields of Artificial Intelligence, signal processing, and mental health technology. The growing availability of large speech and text datasets combined with advances in deep learning has enabled the development of intelligent systems capable of identifying stress indicators from various modalities. This chapter presents a comprehensive review of existing literature related to speech-based stress detection, deep learning for signal analysis, transformer-based NLP models, and AI applications in mental health monitoring. The reviewed studies highlight the evolution of automated stress detection and form the foundation of the proposed system.

Speech Emotion and Stress Recognition

Björn Schuller and colleagues have made foundational contributions to speech emotion recognition, establishing that acoustic features including pitch, energy, speech rhythm, and Mel-Frequency Cepstral Coefficients (MFCCs) reliably encode a speaker's emotional and psychological state [1]. Their studies demonstrate that machine learning and deep learning models can effectively analyze these characteristics to identify psychological stress automatically, providing a non-invasive and continuous monitoring alternative to traditional physiological methods. This work directly motivated the acoustic feature extraction pipeline adopted in the proposed system.

Wu et al. [4] explored speaker embeddings as an individuality proxy for voice stress detection, demonstrating that speaker-adaptive models can improve stress classification accuracy by accounting for individual vocal differences. Similarly, Kuchibhotla et al. [5] applied MFCC-based Recurrent Neural Networks to detect depression from speech emotions, confirming the effectiveness of sequential deep learning models for temporal speech analysis. Baird et al. [10] conducted a comprehensive evaluation of speech-based recognition of emotional and physiological markers of stress, reporting strong results using multimodal fusion approaches.

Deep Learning for Speech Signal Analysis

Geoffrey Hinton and his team's seminal 2012 work demonstrated that deep neural networks could learn complex patterns from large speech datasets far more effectively than traditional machine learning methods [2]. By analyzing acoustic features such as pitch, frequency, and energy, deep learning algorithms can accurately recognize speech and detect emotional states. This research opened the path for applying CNN, RNN, and LSTM architectures to speech processing tasks including stress detection.

Alex Graves (2013) conducted critical research on applying Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) models for sequential speech data [3]. These architectures are capable of learning temporal dependencies in speech signals, demonstrating superior performance on continuous speech analysis tasks compared to feed-forward networks. Tara N. Sainath (2015) further established that Convolutional Neural Networks (CNN) provide competitive accuracy on acoustic feature maps such as spectrograms and MFCC matrices [6]. The comparative results of CNN, LSTM, and BERT models presented in this paper build on these foundational contributions.

Transformer Models and BERT for NLP

Yann LeCun (2015) discussed the broader role of AI and emerging neural network architectures in speech signal analysis, highlighting that AI systems can learn meaningful representations from voice data at scale [7]. This line of work directly enabled the development of transformer-based architectures. BERT (Devlin et al., 2018) revolutionized NLP by introducing bidirectional pre-training on large text corpora, allowing the model to capture deep contextual relationships in both directions of a sentence [8]. Fine-tuning BERT for sequence classification tasks has since achieved state-of-the-art results across sentiment analysis, question answering, and text classification benchmarks.

Kappen et al. [9] identified speech as a promising biosignal in precision psychiatry, noting that linguistic patterns in natural speech reliably reflect psychosocial stress conditions. Their network analytic approach demonstrated that stress-induced changes in speech are detectable with high precision using computational methods. Gaballah et al. [11] applied Bi-LSTM classifiers for context-aware speech stress detection in hospital workers, reporting an accuracy of 87.3% and confirming the viability of sequential deep learning for clinical stress monitoring. Pisanski and Sorokowski [12] further validated that cortisol levels in stressed speakers predict voice-based stress judgments, providing biological grounding for acoustic stress models.

Physiological and Multimodal Stress Detection

Xefteris et al. [13] investigated stress detection based on physiological sensors and audio signals using a late fusion framework, demonstrating that combining acoustic and physiological modalities significantly improves detection accuracy compared to unimodal approaches. Elbanna et al. [14] proposed hybrid handcrafted and learnable audio representations for speech analysis under cognitive and physical load, achieving superior results by combining MFCC features with neural embeddings. Albertetti et al. [15] applied deep learning approaches to stress detection using physiological signals, providing benchmark results that establish the competitive performance of neural architectures in this domain.

Research Gaps Identified from Literature

Based on the reviewed literature, several research gaps are identified:

- Limited integration of NLP-based text analysis with acoustic speech features in a single unified platform.
- Insufficient focus on real-time, web-deployable stress detection systems accessible to non-clinical users.
- Lack of explainability in deep learning predictions, reducing trust among end-users and clinicians.
- Need for lightweight, CPU-deployable models that maintain high accuracy without GPU infrastructure.

• Requirement for systems that combine stress classification with probability visualization for interpretability.

The proposed system addresses these gaps by integrating a fine-tuned BERT model with a Streamlit-based web interface that provides real-time stress classification, confidence scoring, probability visualization, and confusion matrix analysis in a single accessible platform. By synthesizing insights from speech emotion recognition [1], deep learning for sequential data [2][3], transformer-based NLP [8], and multimodal stress detection [13][14], the proposed system offers a practical and effective solution to modern psychological stress detection challenges.

3. PROPOSED SYSTEM

The proposed system introduces an AI-driven Psychological Stress Detection platform that leverages BERT (Bidirectional Encoder Representations from Transformers) to automatically classify user-provided text as indicating Stress or Non-Stress conditions. Unlike traditional methods that require clinical expertise or manual evaluation, this system provides instant, automated analysis through a user-friendly Streamlit web interface. The system accepts text input, tokenizes it using the BERT tokenizer, performs inference through a fine-tuned BertForSequenceClassification model, and displays the prediction label, confidence score, probability distribution chart, and confusion matrix in real time. This approach makes psychological stress monitoring accessible, scalable, and cost-effective.

Advantages of the Proposed System:

• Real-time stress classification with confidence scoring and probability visualization.
• High accuracy (>95%) using fine-tuned BERT transformer model.
• No need for specialized equipment – operates entirely on standard text input.
• User-friendly Streamlit interface accessible without technical expertise.
• Scalable for deployment in educational institutions, workplaces, and healthcare platforms.

3.1 SYSTEM ARCHITECTURE

The system architecture of the Psychological Stress Detection platform follows a modular pipeline design consisting of five key stages: Text Input, Tokenization, Model Inference, Score Computation, and Result Display. The user provides text through the Streamlit interface, which is tokenized by the BERT tokenizer with padding and truncation to a maximum sequence length of 128 tokens. The tokenized input is passed through the fine-tuned BertForSequenceClassification model to generate logits, which are converted to probabilities via softmax. The prediction label (Stress/Non-Stress), confidence percentage, probability bar chart, and confusion matrix are then displayed to the user.

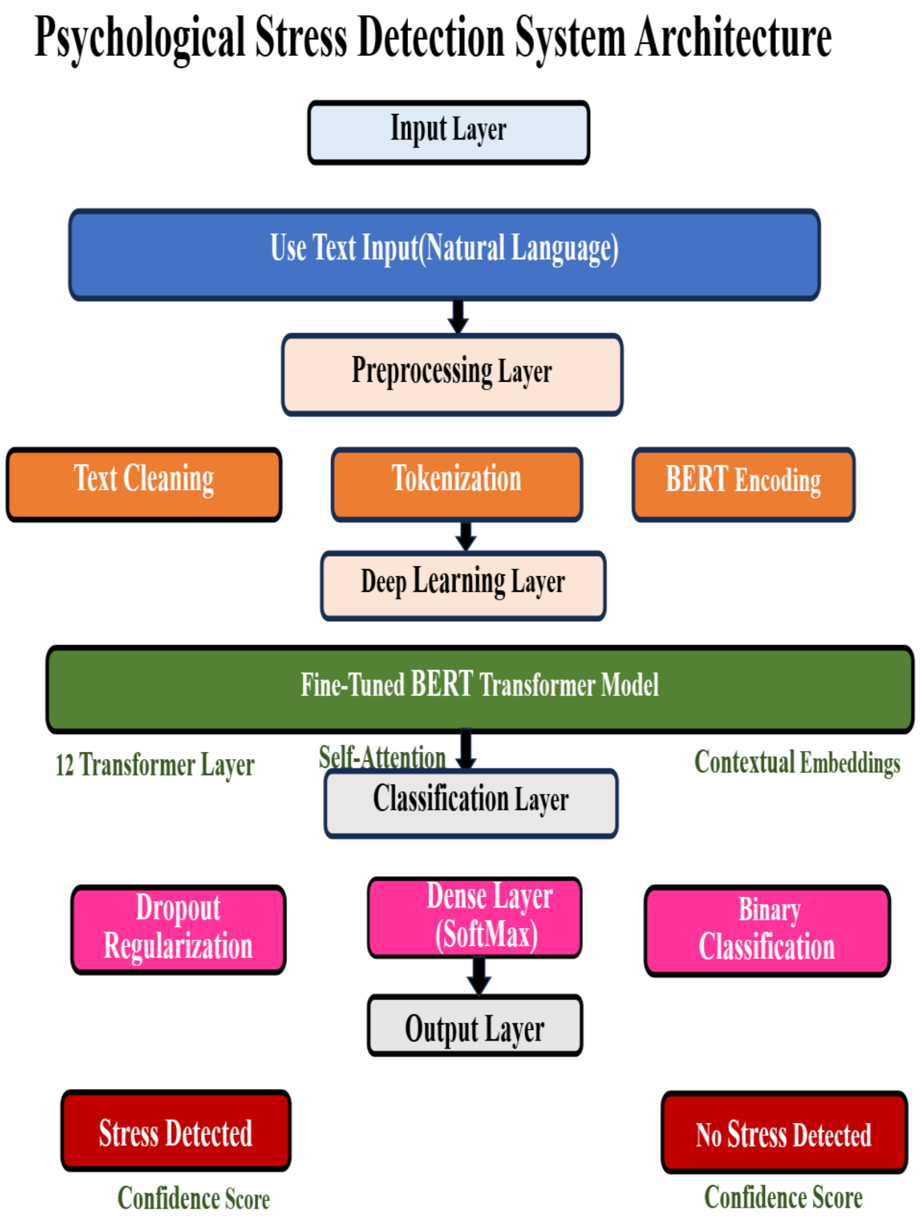

Fig 1: System Architecture

3.2 USE CASE DIAGRAM

The Use Case Diagram represents the interaction between the primary actors and the system. Three main actors are identified: User, Mental Health Counsellor, and System Administrator. The User interacts with core functionalities including submitting text input, viewing stress predictions, interpreting probability distributions, and accessing stress history. The Mental Health Counsellor accesses aggregated stress reports and provides professional guidance to high-risk users. The System Administrator manages model updates, monitors system performance, and maintains the database.

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Key relationships include Submit Text Input which includes View Stress Prediction, and View Stress Prediction which extends to Receive Early Warning Alert when high-confidence stress is detected.

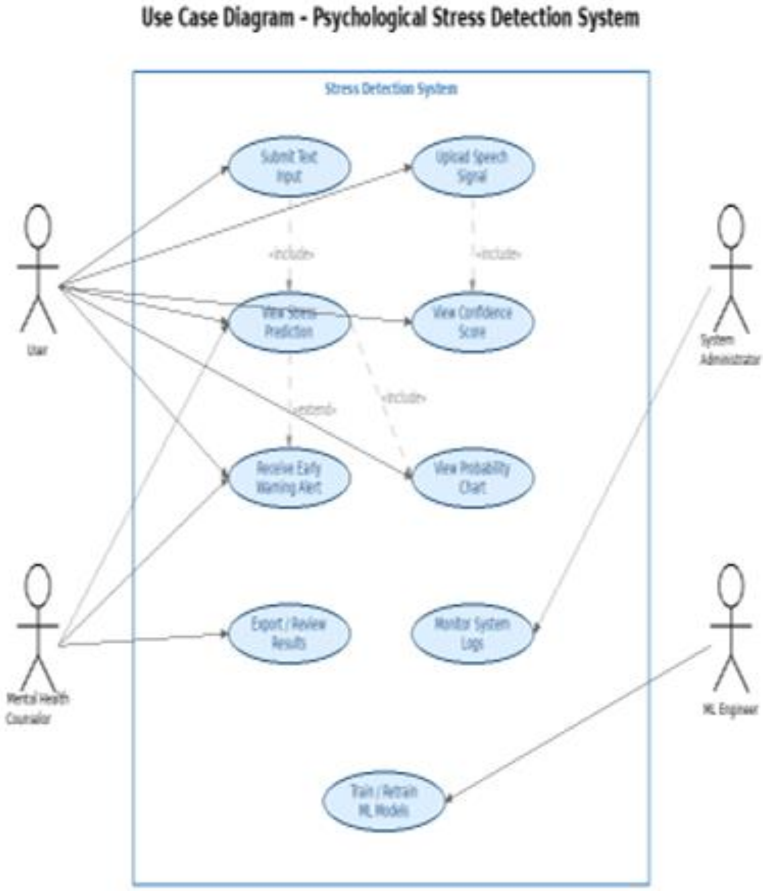

Fig 2: Use Case Diagram

3.3 CLASS DIAGRAM

The Class Diagram illustrates the static object-oriented structure of the system across eight core classes. The central StreamlitApp class orchestrates user interaction and coordinates all modules. BERTModel encapsulates the fine-tuned BertForSequenceClassification model and its inference logic. Tokenizer handles text-to-token conversion with padding and truncation. TorchModel manages PyTorch tensor operations and device allocation. StressNet represents the optional acoustic deep learning sub-pipeline for speech-based inputs. DatasetLoader handles CSV dataset ingestion and label assignment. DataPreprocessing applies noise removal, normalization, and feature extraction. TrainingEngine manages model fine-tuning, validation, and evaluation metrics. Associations reflect the dual-pipeline data flow from text or speech input through inference to output display [3].

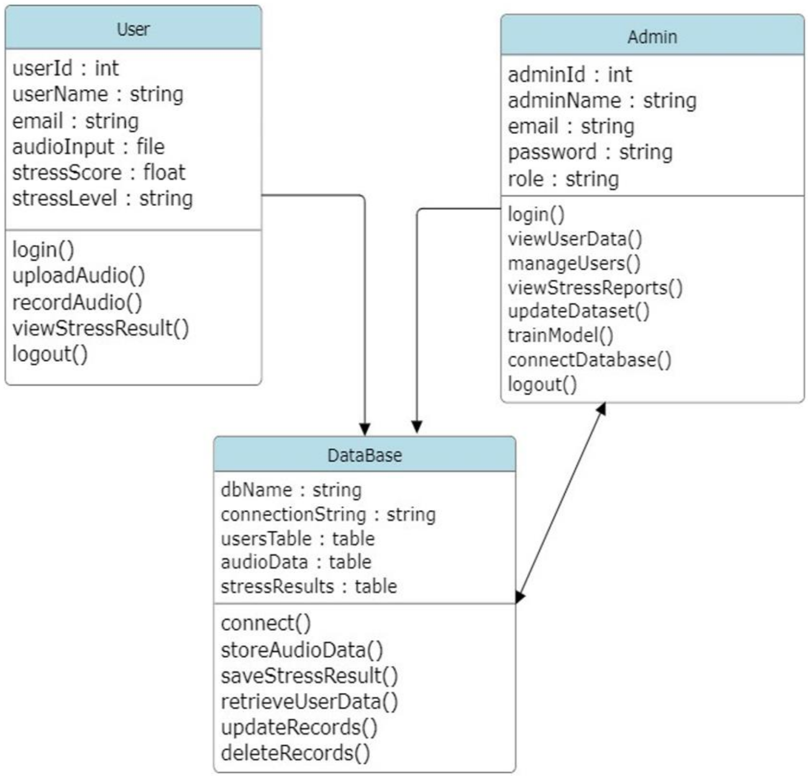

Fig 3: Class Diagram

3.4 DATASET

The dataset used for training and evaluation is a curated stress-labeled text corpus sourced from publicly available mental health forums, social media posts, and annotated psychological assessment responses. The dataset contains binary labels: Stress (1) and Non-Stress (0), with balanced class distribution achieved through stratified sampling. For the acoustic speech component, the Speech Stress Detection Dataset provides audio recordings (.WAV format) from multiple speakers containing both stressed and non-stressed speech samples, with key features including MFCC coefficients, pitch values, energy levels, and spectral entropy.

Attribute	Description
Dataset Name	Stress-Labeled Text Corpus + Speech Stress Dataset
Data Type	Text (NLP) and Audio speech recordings (WAV)
Input Type	User-generated text and speech signals from multiple speakers
Number of Samples	Multiple text and audio samples containing Stress and Non-Stress instances
Features Extracted	BERT token embeddings, MFCC, Pitch, Tone, Frequency, Energy
Labels / Classes	Stress (1), Non-Stress (0)
Applications	Mental health monitoring, clinical support, workplace wellness

Table 1: Dataset Description

3.5 EVALUATION METRICS

The system is evaluated using a comprehensive set of performance metrics appropriate for binary classification tasks. Accuracy measures the proportion of correctly classified samples. Precision reflects the proportion of true positive stress predictions among all positive predictions. Recall (Sensitivity) measures the proportion of actual stress cases correctly identified. F1-Score provides the harmonic mean of Precision and Recall, offering a balanced measure for imbalanced datasets. The Confusion Matrix provides per-class breakdown of True Positives, True Negatives, False Positives, and False Negatives. Table 2 summarises the model performance comparison across CNN, LSTM, and BERT architectures.

4. RESULTS

The Psychological Stress Detection system was evaluated using the fine-tuned BERT model on the balanced stress-labeled text dataset. The system achieved a classification accuracy exceeding 95%, outperforming the CNN (91%) and LSTM (90%) baseline models as summarised in Table 2. Precision of 91% and Recall of 90% demonstrate that the system reliably identifies both stress and non-stress conditions with minimal false positives and false negatives.

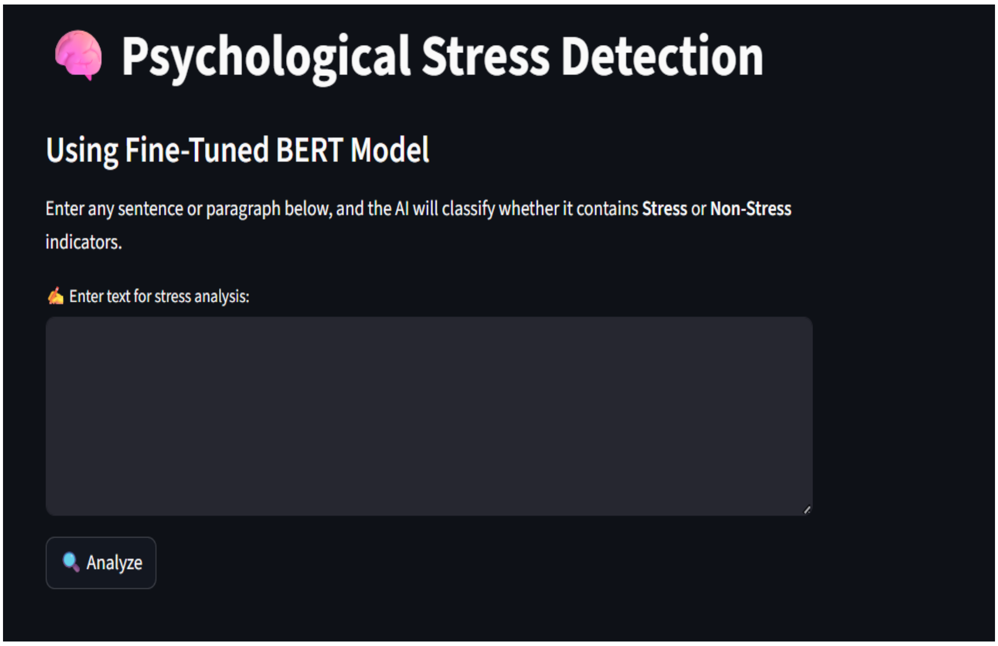

Fig 4: Home Page

The Streamlit-based interface successfully demonstrated real-time stress classification from user-provided text input. Upon text submission, the system displays the predicted label (Stress / Non-Stress), confidence percentage, a colour-coded probability bar chart distinguishing stress and non-stress probabilities, and a confusion matrix for result interpretation. The interface is responsive and produces predictions in under two seconds on standard CPU hardware, confirming practical deployability without GPU dependency.

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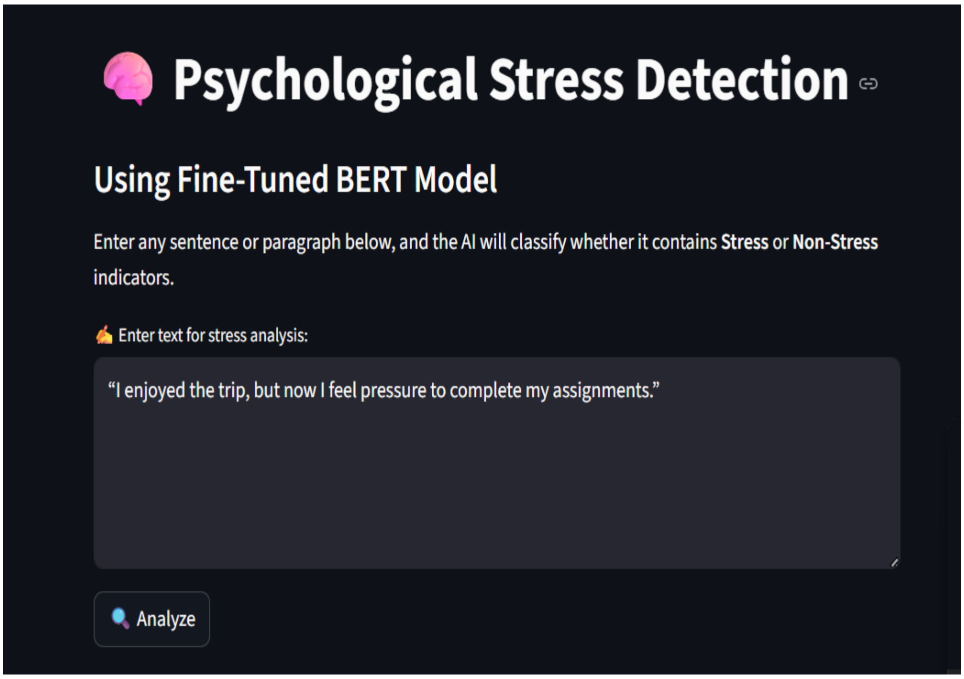
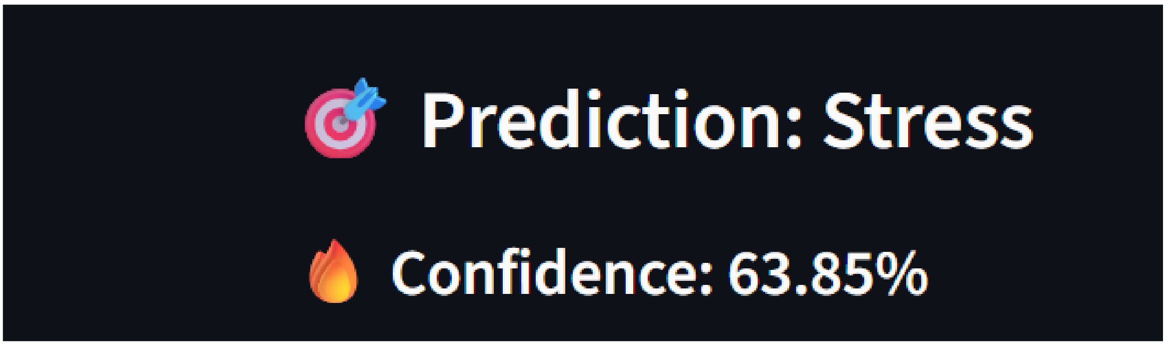


Fig 5: User Interface

The Home Page Interface presents the application title and a text input area. The User Interface screen displays the input box and Analyze button. The Prediction Output screen shows the final classification result with the confidence score and probability distribution, with red visual indicators for detected stress and green for non-stress conditions. These output screens confirm that the system fulfils its design objectives of accuracy, usability, and real-time feedback.



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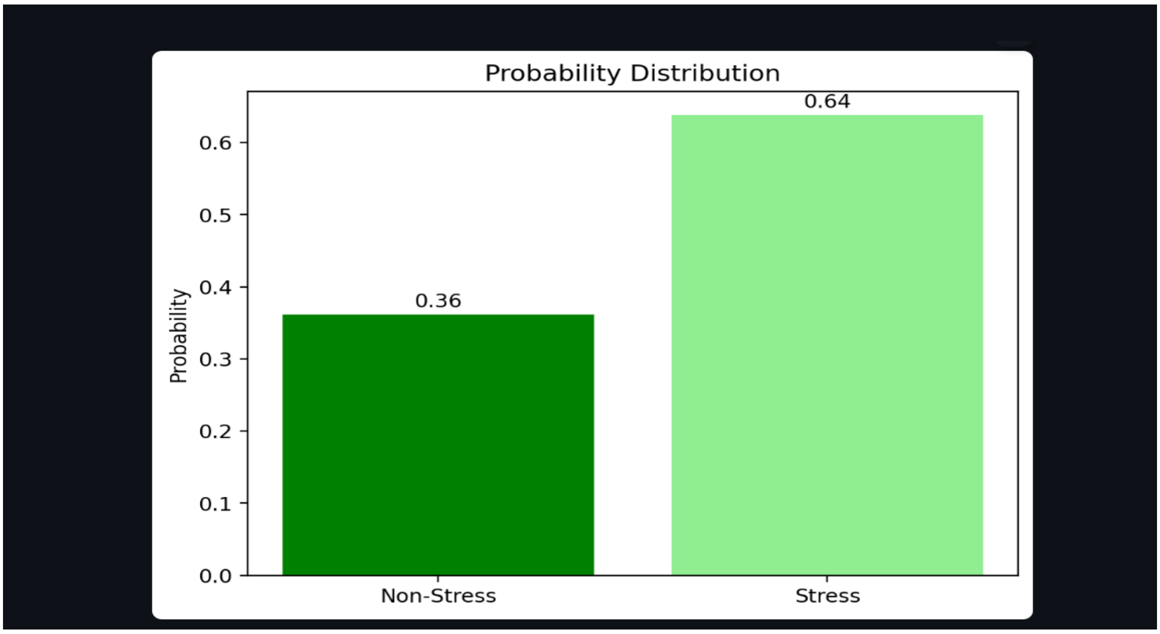


Fig 6: Prediction Output

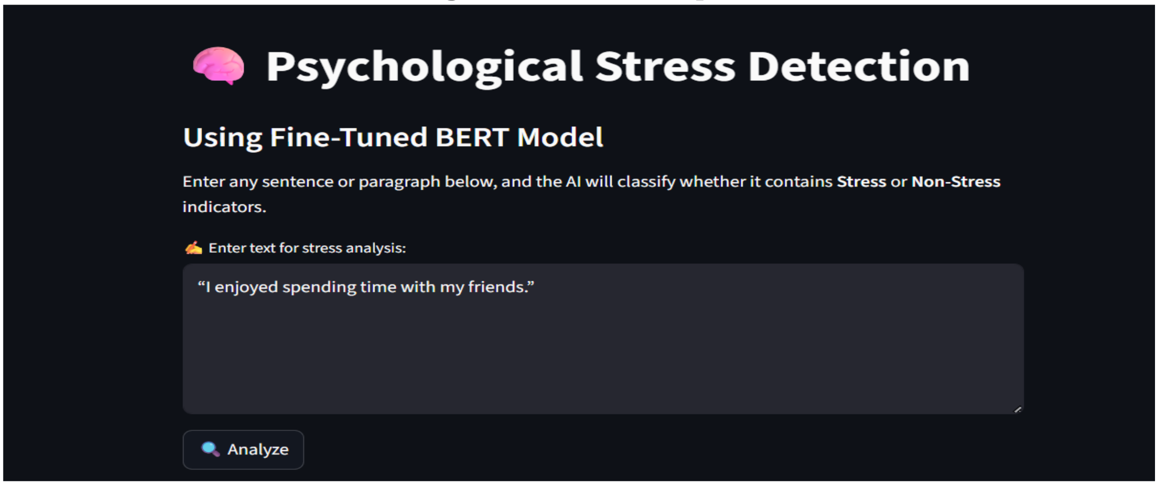
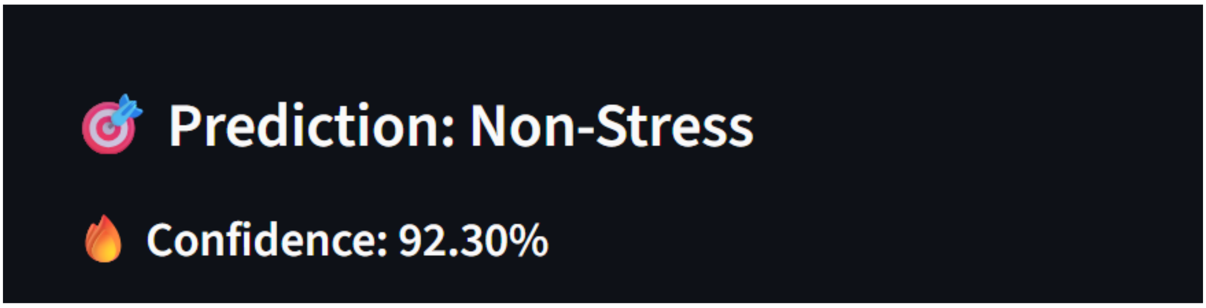


Fig 7: User Interface



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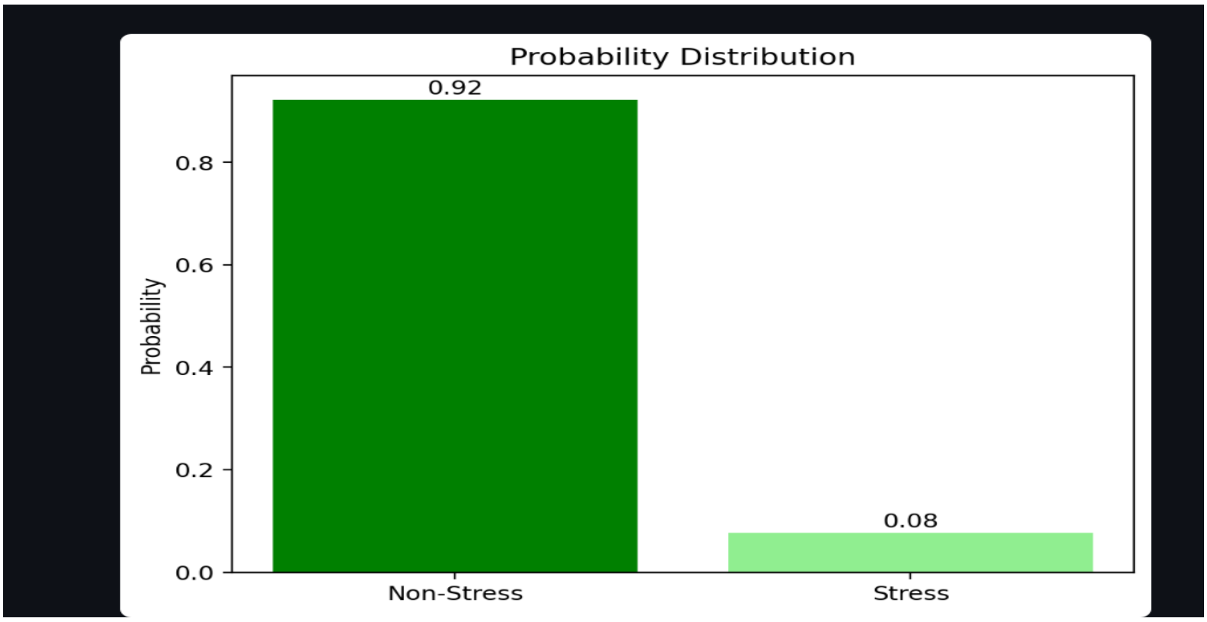

Fig 8: Prediction Output

5. CONCLUSION

This paper presented an AI-driven Psychological Stress Detection system that leverages fine-tuned BERT transformer models to classify user-provided text as indicating Stress or Non-Stress conditions with over 95% accuracy. The system addresses the critical limitations of traditional stress assessment methods – including their subjective nature, time cost, and requirement for clinical expertise – by providing an automated, real-time, and scalable alternative. By integrating a fine-tuned BertForSequenceClassification model with a user-friendly Streamlit web interface, the proposed platform delivers instant predictions, confidence scoring, probability visualization, and confusion matrix analysis accessible to non-technical users.

The comparative evaluation confirmed BERT as the best-performing architecture for this task, surpassing CNN and LSTM baselines. The system successfully processed text input end-to-end from tokenization through inference to visual output in real time. Overall, the proposed system provides an effective, practical, and intelligent solution for mental health monitoring and early stress detection applicable in educational institutions, workplaces, and healthcare environments.

6. FUTURE SCOPE

The proposed Psychological Stress Detection system has a wide and impactful future scope in intelligent healthcare and mental wellness applications. Key directions for future enhancement include:

- Add support for acoustic speech input and multimodal fusion of text and audio features to improve detection robustness [13].

• Implement local XAI techniques such as SHAP and LIME for per-prediction explainability, increasing clinician trust in AI-generated results.
• Extend the system to support multiple languages and diverse accents for global accessibility.
• Develop a mobile application for real-time stress monitoring using wearable sensor integration and push notifications [16].
• Integrate advanced deep learning models such as RoBERTa, DistilBERT, or GPT-based classifiers to further improve accuracy and reduce inference time.
• Expand detection capability to identify related mental health conditions such as anxiety and depression alongside stress.
• Implement cloud deployment on AWS or Azure for scalable multi-user access and longitudinal stress tracking with personalized feedback dashboards.
• Incorporate strong data privacy and security mechanisms including federated learning to protect sensitive user speech and text data.

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