Volume 11, Issue 4, April – 2026 International Journal of Innovative Science and Research Technology
ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26apr839

Real-Time Social Media Emotion Analysis for Suicide Prevention

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Publication Date: 2026/04/24

Abstract: One of the biggest challenges nowadays is suicide and careful mental health care is urgently needed. The available models of emotion analysis are usually not reactive in real-time, not culturally adaptable and interpretable which reduces their effectiveness in suicide prevention via social media monitoring. This paper proposes a new Hybrid Adaptive Emotion Analysis Model (HAEAM) where the multimodal data are used: text, audio and visual combined with CNNs, BiLSTM with attention and weighted fusion to provide a better perception of detection of emotions in real-time. The model presents a context-sensitive adaptivity module of platform and cultural sensitivity and brings in Explainable AI (XAI) functions that guarantee transparency and ethical compliance.

Keywords: *Suicide Prevention, Emotion Analysis, Real-Time Detection, Multimodal AI, Explainable AI.*

How to Cite: Aadya Mishra; Charu Srivastav; Dr. Shalini Lamba; Rinku Raheja (2026) Real-Time Social Media Emotion Analysis for Suicide Prevention. *International Journal of Innovative Science and Research Technology,* 11(4), 1722-1728. https://doi.org/10.38124/ijisrt/26apr839

I. INTRODUCTION

➢ *Background*

Suicide is a critical global health challenge, claiming around 746,000 lives yearly which is equal to one life lost every 43 seconds [1]. Since 1990, the worldwide suicide rate has decreased by nearly 40%, but Central Latin America and high-income North America have experienced increase in suicide of 39% and 7% respectively[2]. In addition, using firearms to commit suicide is common for men in the country, accounting for 55% of such deaths[3]. Even though May is Mental Health Awareness Month, focusing on the issue, most common counselling methods do not connect with the people who need help most[4]. As need for additional support is growing day by day, it's important to use technology to identify people who might be struggling or in suffering before it becomes a bigger issue. [5]

➢ *Problem Statement*

One of the key limitations of existing systems for emotional detection is temporal latency, most of the models focus on analysing historical data instead of real-time inputs[6]. Due to this delay, there may be fewer chances to help someone who talks about their worries online[7]. Furthermore, the current models do not include understanding of cultural differences, such as sarcasm and focus almost solely on strict words and their meanings[8]. Such systems wrongly detect around 42% of expressions important for recognizing suicidal thoughts for this reason only [9]. Using data sets based on western information can lead to poorer results in regions with higher suicide rates, like Ecuador. In Ecuador, the number of suicides among women has increased by 123%.[10]

➢ *Research Objectives*

The purpose of this study is to discover the main weaknesses present in emotion analysis models, mainly regarding the time and circumstances they take into account[6]. Then, we will build a new system that helps detect thoughts of suicide in a real-time manner from social media. It will feature NLP processing along with the fusion of information form text with images and metadata and engines that can interpret emotions accurately from the context. The proposed model should show results that line up with data on known risk factors for suicide, such as emotional volatility.[5]

➢ *Significance of the Study*

The potential impact of this research could be significant. Being able to spot signs of danger in real time may save lives. For example, when people call crisis hotlines, using speech emotion recognition has achieved up to 73.13% accuracy in the cases studied so far. [11]. By cutting down how long it takes to get results by up to 83%, quick analysis helps make it easier to prevent accidents before they happen. [7] Additionally, our proposed model will be able to work well in lots of different cultures and languages, which can really help in places where there aren't many mental health services.[4]

➢ *Research Questions*

- What are the key limitations of the existing emotion analysis models for suicide prevention?

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26apr839

- What components are essentially required for developing an effective real-time social media emotion analysis model?
- How can the proposed model enhance the accuracy and speed of suicide risk detection?

Looking into these questions, the study aims to move forward with technology based real time support that promotes better and more inclusive care for people experiencing suicidal thoughts.[5][10][11]

Figure 1 illustrates the comparison between the AI-based model and traditional models. This graph was made in Python using Matplotlib. AI-driven methods show superior performance in accuracy, cultural sensitivity because it possess the ability to analyse large datasets.

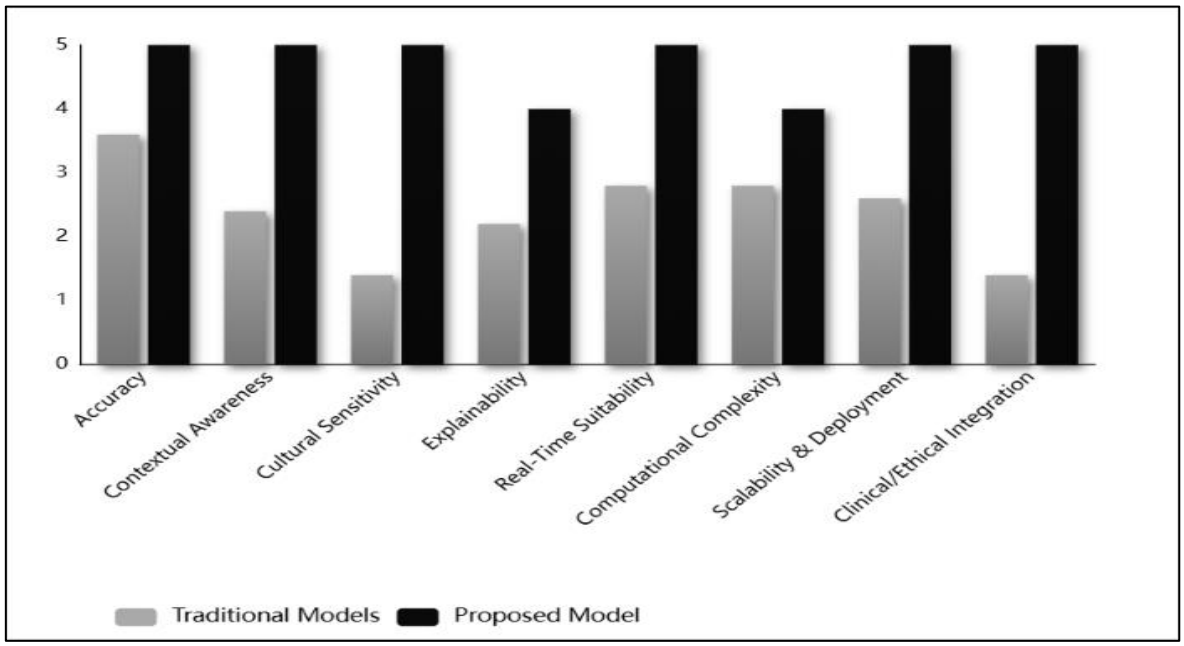

Fig 1 Comparison of AI Model and Traditional Method

II. RELATED WORK

A. Explainable AI (XAI) Ensemble Framework:

Using the Explainable AI (XAI) Ensemble Framework, it is possible to identify what type of thinking someone is having, such as suicidal or not with a high F1-score of over 95%. Making sense of it is one of its greatest advantages. Through SHAP values, mental health experts can discover which features play a role in the system's decisions and therefore rely more on it. Furthermore, the model is effective in processing data as it comes in, so intervention can be made swiftly. Ensembles use results from several models to improve the performance made by the separate models.[12][13][14] The final prediction $\hat{y}$ is calculated as the average of individual model predictions:

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N} fi(x)$$

Where:

- $\hat{y}$ is final prediction,
- N is the number of models in the ensemble,
- $fi(x)$ is a prediction of the $i-th$ Model for input x.

Still, there were some issues with this framework. The group approach needs a lot of computing power. The performance of the technology often depends on the quality and fairness of the data it learns from, so biased data can cause its results to be twisted. But there are still some challenges that experts have yet to resolve. Sometimes, the model does not understand refined ways that express distress, like sarcasm and cultural terms, as these require more understanding of the situation.

B. CNN-BiLSTM Hybrid Model with Attention Mechanism:

The CNN-BiLSTM Hybrid Model with Attention Mechanism can better understand the emotional features of text, designed with both local and long-range consideration in mind. Having this attention feature, the model is able to pick out high-risk phrases and identify threats more easily.[13][15]

➢ *Mathematical Formulation:*

- *CNN Feature Extraction:*

The CNN component processes input text to capture local dependencies using the ReLU activation function:

$$h_i = ReLU(W . x_i + b)$$

Where:

- ✓ hi = Output feature from CNN
- ✓ W= Weight matrix
- ✓ x_i= Input Word embedding
- ✓ b= Bias

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- *BiLSTM Hidden State:*

The BiLSTM layer captures long-term dependencies by combining forward and backward hidden states:

$$h_t = BiLSTM(h_{t-1}, x_t)$$

Where:

✓ h_t= Hidden state at time t
✓ x_t= Input at time t

- *Attention Weight Calculation:*

The attention mechanism assigns weights to each word based on its importance, calculated as follows:

$$\alpha_t = \frac{exp(e_t)}{\sum_{j=1}^{T} exp(e_j)}$$

Where:

✓ α_t = Attention weight
✓ e_t = Alignment score at time t

The CNN extracts useful words and parts of the text, while the BiLSTM looks at the overall patterns that appear in the sequence. The model decides which features relate the most to suicidal thoughts with the help of an attention mechanism, and so it pays close attention to these words or sections.

Yet, the model is complex and often needs many labelled datasets for training, which sometimes do not exist for rare languages or dialects. Furthermore, complex architecture means it takes more effort and time to implement and keep it operational.

Even though the model handles data fast, the high demand for computations is still a challenge for running the same applications in real time on different platforms. It becomes a challenge to apply the model broadly when dealing with quick and constant changes in social media.

C. Multilingual SVM-Based Classification:

This model can analyse sentiments in several languages and play an important role in filling a significant gap in suicide prevention efforts within multilingual contexts. SVMs are simple and efficient, but deep learning models are not, because they use more power than SVMs. SVMs can be implemented easily and without much computing power when compared to deep learning models.[12][13]

➢ *Mathematical Formulation:*

- *SVM Decision Function:*

Support Vector Machine (SVM) uses a decision function to classify data:

$$f(x) = sign\left(\sum_{i=1}^{n} \alpha_i \, y_i K(x_i, x) + b\right)$$

Where:

✓ $f(x)$ = Decision function
✓ α_i = Lagrange multipliers
✓ y_i = Class label
✓ $K(x_i, x)$ = Kernel function
✓ b = Bias term

By finding the optimal hyperplane, the decision function separates the data by increasing the distance between the two classes. Still, there are certain limitations to the model. Dependence on vocabulary can lead to overlooking key details that help interpret a person's feelings. The results can vary widely depending on the language and culture found in the posts. Because of this variability, it can be challenging to classify the cultural expressions of both distress and humour accurately because they often don't come across well in other languages.

D. Real-Time NLP Predictive Pipeline:

The Real-Time NLP Predictive Pipeline allows for continuous monitoring, which instantly shows an alert when someone is having emotional problems. The geolocation technology helps make the most vulnerable individuals in areas lacking mental health care get assistance quickly.[16][17] Still, adding geolocation systems to platforms raise issues about protecting user privacy and safety, and these must be solved carefully.

$$\Delta S = \frac{S_{t+1} - S_t}{t + 1 - t}$$

Where:

✓ ΔS= Sentiment Change rate
✓ S_t= Sentiment score at time t
✓ S_{t+1}= Sentiment score at time t+1

The model looks at changes in sentiment rates to find unexpected shifts that could signal a crisis. While the pipeline tries to minimize false positives better than static models, there is still a chance for errors. In turn, this situation aims unnecessary measures or bypasses a chance to support people who require help. Also, the model can find it difficult to understand all the different emotional aspects that people post on social networking sites.

E. Multimodal Emotion Fusion Model:

This model considers text, images and videos information together to give a complete picture of what users are feeling. This enables that model to sense small signs of distress. Its usability for many different platforms makes it more helpful since it can look at content of various social media networks.[12][17]

➢ *Mathematical Formulation:*

- *Multimodal Fusion:*

To effectively combine various modalities, the model uses weighted averaging:

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26apr839

$$F = \sum_{m=1}^{M} w_m \cdot f_m$$

Where:

- ✓ F= Fused emotion score
- ✓ w_m = Weight assigned to modality m
- ✓ f_m= Emotion score from modality m

The model ranks data sources by weighing each modality, so that more helpful sources are considered first.

But, having to deal with its complexity and the need for significant resources creates great difficulties in managing and updating the model. Collecting necessary multimodal data for training is a struggle in regions that do have sufficient internet access or social media use. Dealing with various types of data almost instantly is still a significant challenge which makes it tough to provide timely help during critical situations.

III. PROPOSED METHODOLOGY

Considering the challenges and the limitations of the existing AI models for analysing social media data for suicide prevention, we propose a new model: Hybrid Adaptive Emotion Analysis Model (HAEAM). [5][18]

- Aim: To enhance emotions identification, fit with possible linguistic and cultural combinations, offer quick response and pay attention to ethics and transparency.[4]

➢ *Architecture of the Proposed Model:*
The model consists of three core components:

- *Hybrid Feature Extraction:*

Model will use data from multiple resources including text, audio and visual elements. The model is built using a fusion of deep learning techniques.

- ✓ Application of CNN for interpreting emotions in pictures.
- ✓ BiLSTM with attention is used to understand the context from text and speech resources.
- ✓ The model uses a weighted fusion layer to join different types of information in the most effective way.

- *Equation:*

The final emotion score is derived using the Weighted Feature Fusion strategy:

$$F = w_1 F_{text} + w_2 F_{audio} + w_3 F_{image}$$

Where:

- ✓ w_1, w_2, w_2= Weights assigned to each modality.
- ✓ F_{text}= Text emotion score from BiLSTM.
- ✓ F_{audio}= Audio sentiment score.
- ✓ F_{image}= Visual emotion score from CNN.

This strategy guarantees that every data source is used in a way that improves the accuracy of predictions.[12][18][19]

- *Context-Aware Adaptation Module:*

This module trains the model on contextual cues like the platform (Reddit, Twitter) and regional nuances in language. Using pre-trained models for transfer learning on specific domain data helps ensure cultural sensitivity. The adaptation process consists of the following steps:

- ✓ Language Detection: Determining the main language utilized.
- ✓ Sentiment Calibration: Sentiment interpretation adjustment in accordance with cultural nuances.
- ✓ Platform-Specific Fine-Tuning: Turning into platform-specific text patterns (example – hashtags, abbreviations).[6][13]

- *Explainable and Ethical AI Integration:*

The model combines explainable AI methods such as SHAP to produce human-readable explanations of predictions. This is necessary for upholding user trust and ethical adherence.

- Ethical Standards: Adding detection and mitigation of bias to avoid skewed results from minority group data.
- Transparency Metrics: Providing interpretability scores to show which features most influenced a decision.[13][14]

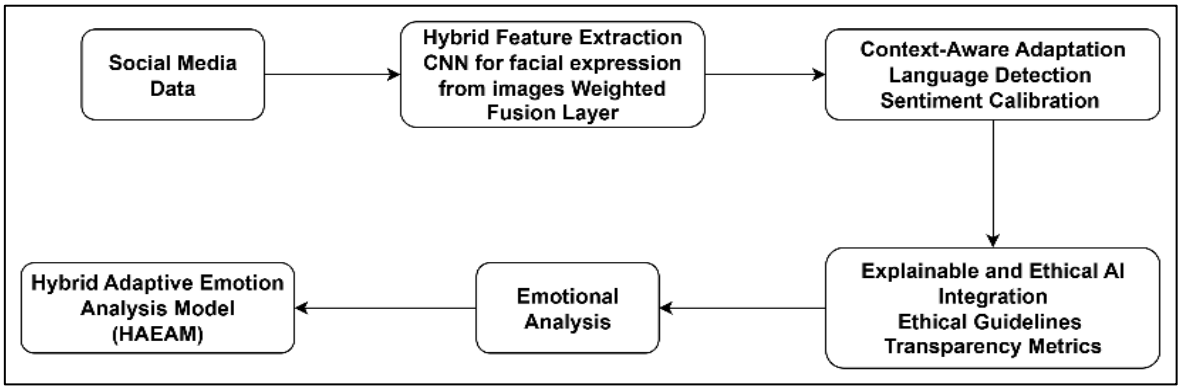

Fig 2 Flowchart of the Hybrid Adaptive Emotion Analysis Model (HAEAM) for real-time suicide prevention.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26apr839

➢ *Required Datasets and Preprocessing:*

- *Datasets:*

The model needs varied and representative datasets, such as:

✓ Text Data: Posts from Twitter and Reddit for text analysis.
✓ Audio Data: Includes recordings of mental health support calls (e.g. DAIC-WOZ).
✓ Image Data: Frames from facial expression datasets (e.g. CASME).
✓ Multimodal Data: certain datasets in MuSe are created using text, audio and visual details to analyse sentiments.[17][18]

Figure 3, depicts the ratio of text data, audio data, image data and multimodal data we can use in the HAEAM. This is a hypothetical graph, generated in Python using matplotlib.

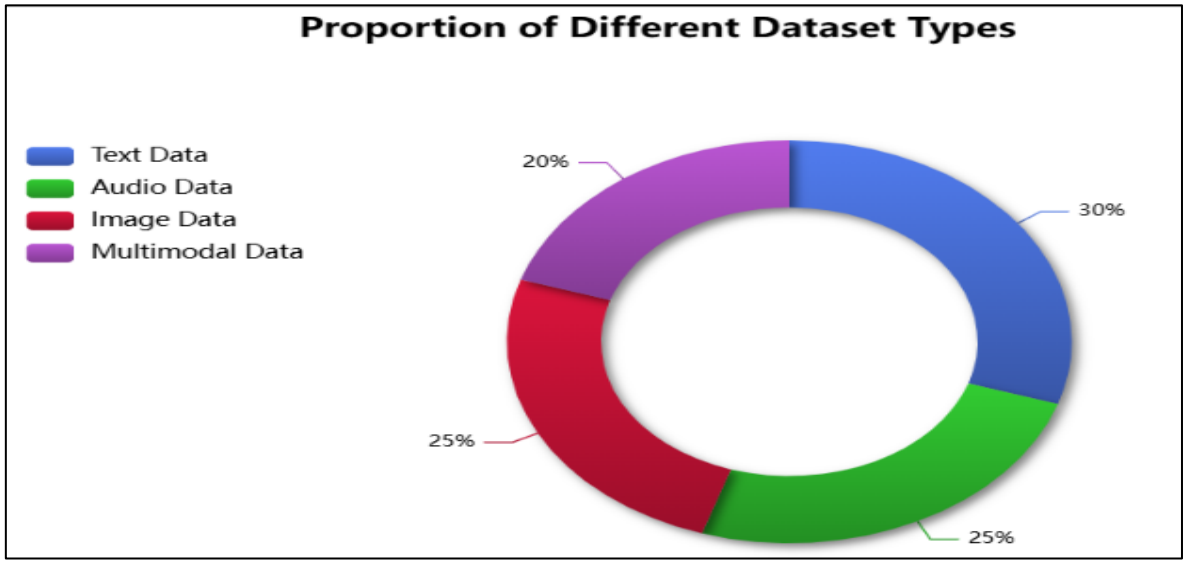

Fig 3 Proportion of Different Dataset.

- *Preprocessing:*

✓ Text: Tokenization, stopword removal and sentiment labelling
✓ Audio: Supports noise reduction and changing speech into text.
✓ Image: Frame extraction and normalization.
✓ Augmentation: GANs to create synthetic instances for underrepresented data categories.[19]

➢ *Potential Improvements:*

- Real-Time Analysis: Applying advanced techniques to analyse data instantaneously.
- Cross-Platform Integration: The model should adapt to be available on several social media sites.
- Improved Accuracy: To minimize the impact of language bias methods from domain adaptation will be used.
- Ethical Safe-Guards: Adding ways to spot biased decisions and to explain the reasoning clearly. [13]

➢ *Theoretical Framework*

This study is based on affective computing, real-time emotion recognition and ethical design in AI which from the main foundation of the proposed Hybrid Adaptive Emotion Analysis Model (HAEAM).

- *Emotion Recognition and Affective Computing:*

Machine that uses affective computing are capable of understanding human emotions. It is common for these approaches to recognize emotions from written texts in samples but not all expressions are easy to catch on social media. Using natural language together with analysis of sound and images gives HAEAM a greater ability to interpret emotions in AI.[19]

- *Multimodal AI for Contextual Understanding:*

Modern systems now combine information from text, speech and visual cues to give a well-rounded view of emotions. However, most existing models work by processing the inputs without change. HAEAM achieves this by combining immediate pipelines and a smart module that interprets data from every background and language. As a result, the model will be able to recognize unique situations and differences among platforms.[6]

- *Explainable and Ethical AI:*

The primary concern with using AI in suicide prevention is that its decision-making processes are difficult to clear. HAEAM addresses this through explainability techniques such as SHAP, which clarify which features influenced predictions. This model also adds the feature of fairness auditing and bias mitigating to ensure ethical behaviour specifically when used with diverse populations.[14]

Together, the theories ensure that the system is consistent, transparent and flexible enough to enhance real-time suicide prevention efforts. [18]

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26apr839

Table 1 Methodology Comparative Analysis

Feature	XAI Ensemble Model	CNN-BiLSTM with attention	Multilingual SVM	Real-Time NLP Pipeline	Multimodal Emotion Fusion	Proposed HAEAM Model
Data Modalities	Text (structured and weighted)	Text (sequential, contextual)	Multilingual Text	Text with geolocation	Text, audio, video	Text, audio, image
Accuracy	High (F1> 95%)	High for sequential emotional states	Moderate to High (language-dependent)	Moderate (improved over static models)	High (holistic analysis)	High (via weighted multimodal fusion)
Contextual Awareness	Moderate	High (attention-focused)	Low	Moderate (uses sentiment change rates)	Moderate (limited by real-time feasibility)	Very High (context-aware adaptation module)
Cultural Sensitivity	Limited (Western dataset bias)	Limited (data-driven, not adaptive)	Moderate (language-based)	Moderate (location-aware)	Low (cultural differences underrepresented)	Very High (transfer learning for local contexts)
Explainability	Strong (SHAP values)	Moderate (some interpretability via attention)	Low (classic SVM)	Low to Moderate	Low (complex fusion layer)	Strong (SHAP + ethical compliance metrics)
Real-Time Suitability	High (streaming-capable)	Moderate (high computational load)	High (lightweight model)	High (designed for continuous input)	Low (heavy processing load)	High (optimized real-time pipelines)
Computational Complexity	High	High	Low	Moderate	Very High	High (balanced with optimization strategies)
Scalability & Deployment	Moderate (needs resources)	Moderate (deep model)	High (scalable across regions)	High	Low (data & resource-intensive)	High (scalable)
Clinical/Ethical Integration	Moderate (transparent, but needs validation)	Low (limited interpretability)	Low	Low (privacy concerns)	Low (black-box design)	High (built-in ethical guardrails and explainability)

IV. CONCLUSION & FUTURE SCOPE

The Hybrid Adaptive Emotion Analysis Model (HAEAM) improves real-time detection of suicidal emotions on social media by integrating text, audio and visual data with context-aware adaptation and explainable AI. The model will deal with the problem of inaccuracy, lack of cultural sensitivity, and transparency found in existing models. HAEAM can analyse different types of data in real time and provide clear results. This makes it useful for taking quick action to prevent suicide among different groups and on various platforms. It provides a scalable solution to assist mental health professionals in intervening earlier and more effectively.

Future development should emphasize growing varied datasets, streamlining multimodal fusion for rapid processing, and implementing robust privacy and ethical protections. Field checking with mental health experts and social media platforms is needed to validate real-world performance. In addition, the model can improve as different social media trends and styles of language emerge.

With these improvements, HAEAM might be used effectively to address suicide prevention anywhere in the world.

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