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CONFERENCE PAPER

EARLY DETECTION OF DEPRESSION VIA SOCIAL MEDIA

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Abstract

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The pervasive nature of social media has fundamentally altered the landscape of human communication, leading to a profound reliance on digital platforms for emotional expression. This increased digital footprint provides a critical opportunity for the early detection of depressive states, which have seen a correlated rise with social media usage. This research proposes a computational framework utilizing Natural Language Processing (NLP) and Deep Learning to serve as a Decision Support System (DSS) for counselors, psychologists, and criminal investigators. By employing Word2Vec embedding techniques integrated with a hybrid Convolution Neural Network (CNN) and Long Short-Term Memory (LSTM) architecture, we analyze textual data to identify latent indicators of mental health decline. Our model evaluates the effectiveness of context-free embeddings in classifying sentiment within large-scale social media datasets. The results established in this study provide an empirical baseline for automated mental health monitoring, underscoring the trajectory from static embeddings toward sophisticated contextual modeling.

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Introduction:-

Social media has evolved into a ubiquitous medium for digital self-disclosure, yet it frequently precipitates a destructive "validation cycle." Users often feel an inherent compulsion to broadcast personal experiences to secure social approval; however, the persistent exposure to the curated successes of peers frequently engenders envy, low self-esteem, and exacerbated stress levels. Furthermore, while clinical depression is typically associated with physical social withdrawal, a distinct paradox exists where affected individuals significantly increase their digital expression to seek peer support or document their internal struggle. The primary obstacle in automated detection is the profound discrepancy between an individual's outward digital persona and their internal psychological state. As depicted in Figure 1 of this study (representing a tweet where the text acknowledges crying and pain while the user "just smiles"), a user may project a facade of happiness—masking severe internal pain and suicidal ideation with cheerful visual cues.

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This phenomenon justifies the necessity for automated textual analysis, as visual signals are often deliberately misleading. Consequently, this research focuses on the classification of early depressive indicators within textual data. We utilize Word2Vec, Glove, and Fast Text embedding systems, with a specific focus on CNN-based sentence modelling to capture the nuanced features of sentiment in its premature, non-clinical stages.

Literature Review and Gap Analysis:-

The intersection of computational linguistics and mental health has yielded several notable methodologies:-

Trotzek et al.: Utilized CNN architectures and the Early Risk Detection Error (ERDE) metric to identify depressive indicators through various word embedding technique.

Jadhav et al.: Developed a Decision Tree classifier applied to the Mood Disorder Questionnaire. This approach focuses on identifying significant features within self-reported data to detect Bipolar Disorder.

Seah et al.: Leveraged Latent Dirichlet Allocation (LDA) on Reddit corpora to apply topic modelling, successfully discovering the linguistic contexts in which suicidal ideation typically occurs.

Gap Identification:-

Despite the progress in the field, existing models exhibit specific limitations that this research seeks to address:-

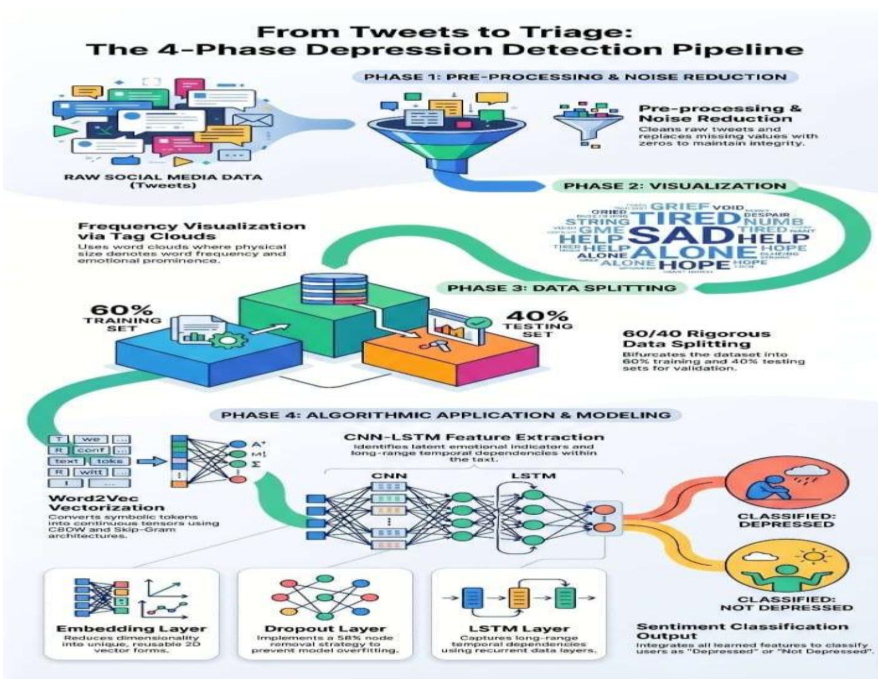
Unidirectional Constraints: Many established models, such as early iterations of OpenAI GPT, utilize a left-to-right flow. This unidirectional pre-training limits the model's ability to synthesize the full semantic meaning of representations.

Shallow Bidirectionality: Architectures like ELMo, while bidirectional, essentially concatenate independent forward and backward models. This shallow integration often fails to capture the deep, interdependent contextual nuances found in emotionally complex conditions.

Contextual Complexity: Depression is rarely signalled by isolated keywords; it requires deep contextual modelling to identify the subtle relationships between past and future tokens in a sequence.

Proposed System Architecture:-

The proposed architecture is designed as a multi-stage pipeline that transforms raw linguistic input into differentiable tensors for high-dimensional classification.



Data Pipeline and Pre-processing:-

The workflow is categorized into four essential technical phases:-

Pre-processing: Raw social media data (tweets) undergo rigorous cleaning. This includes the removal of noise and the handling of missing data, where NA values are replaced with zeros to maintain dataset integrity.

Visualization: Data distribution is analyzed through "Tag Clouds" (Word Clouds) and graphical frequency plots to identify the prominence of metadata related to emotional states.

Data Splitting: To ensure rigorous validation, the dataset is bifurcated into a 60% training set and a 40% testing set .

Algorithmic Application: In this final stage, the symbolic tokens are transitioned into the neural architecture, moving from the vector space to the CNN-LSTM layers for feature extraction and classification. Module I: Word2Vec Embedding Word2Vec is implemented as a shallow, two-layer neural network designed to reconstruct linguistic contexts. This transition is foundational; vector embeddings convert discrete, symbolic linguistic tokens into continuous, differentiable tensors, which are the prerequisite for the mathematical operations within a neural architecture. We utilize two primary architectures:

Continuous Bag of Words (CBOW): Predicts a target word based on the window of its surrounding context words.

Skip-Gram: Uses a single target word to predict the surrounding window of context words by positioning words in a high-dimensional vector space, Word2Vec ensures that emotionally related terms (e.g., "lonely," "low," "suicidal") are located in close proximity based on their shared contextual distribution.

Module II: Convolutional Neural Network (CNN) Design:-

The system utilizes a feed-forward CNN architecture to learn specific properties from the textual data.

The layers and their specific functions are detailed below:| Layer | Function || ------ | ||

Embedding Layer | Facilitates dimensionality reduction, mapping the large-scale corpus into a 2D vector form where each word receives a unique, reusable embedding.

|| **Dropout Layer** | Implements a 50% node removal strategy during the training phase to mitigate overfitting and eliminate statistical noise within the network.

|| LSTM Layer | Comprises two recurrent layers designed to capture **long-range temporal dependencies** . Includes a 20% dropout rate for recurrent data to support robust sequence prediction.

|| Dense Layer | The final fully-connected layer that integrates all learned features to produce the ultimate classification (Depressed vs.
Not Depressed). |

Experimental Setup and Results:-

Environment and Dataset:-

Hardware: Intel Core i7 processor with 8GB of RAM.

Environment: Microsoft Visual Studio IDLE 3.6 (64-bit).

Dataset: Sentiment 140 dataset, containing 1.5 Lac (150,000) records.

Features: The model extracts and processes Context ID, Timestamp, Username, and Comments.

Performance Metrics:-

The empirical evaluation of the hybrid model focused on its capacity to distinguish between positive and negative sentiment markers. The experimental results are as follows:

Accuracy: 52.16%

Loss: 69.27%To interpret these findings, Tag Clouds were utilized as a primary visualization tool. In these clouds, the physical size of a word denotes its frequency and importance within the dataset. For negative sentiment metadata, terms such as "sad," "miss," and "work" appear with high prominence, providing a graphical representation of the linguistic markers associated with depressive states.

Conclusion and Future Work:-

This study establishes that the integration of Word2Vec embeddings with CNN-LSTM architectures provides a viable, though baseline, framework for the early detection of depression. While the accuracy of 52.16% reflects the challenges of using context-free embeddings for complex psychological states, it confirms the utility of textual analysis over visual facades. The next phase of this research will involve a transition from context-free models to bidirectional contextual architectures. Specifically, we intend to implement **BERT** (Bidirectional Encoder Representations from Transformers). This shift will allow for the analysis of depression indicators over longitudinal periods, providing mental health professionals with a significantly more sophisticated and accurate Decision Support System.

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