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FACIAL EXPRESSION ANALYSIS WITH HAAR CASCADE FOR AUTOMATED DETECTION OF DEPRESSION

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Abstract :

Depression is a leading cause of mental health disorders and affects millions worldwide. Early detection and intervention can play a crucial role in improving patient outcomes. This paper proposes a Machine Learning-based Depression Detection System that utilizes facial expression analysis, text mining, and voice-based emotion recognition to assess depression levels among users. The system employs the Haar Cascade Classifier for facial detection, the Xception CNN model for emotion recognition, and speech recognition algorithms for voice-based analysis. Depression is a common mental health problem that often goes unnoticed when using traditional clinical methods. With the increasing use of social media platforms like Twitter, Reddit, Facebook, Instagram, and Weibo, new ways have emerged to detect signs of depression using Machine Learning (ML) and Deep Learning (DL). These technologies help analyze how people behave and communicate online to identify possible symptoms more accurately. Over time, many techniques have been developed for this purpose, but finding all the relevant studies is difficult because research in this area is growing quickly, and search systems often miss useful papers. Although some review articles already exist, many do not clearly explain how this field has evolved, what new techniques are being used, or what challenges still remain. This paper aims to fill that gap by giving a detailed overview of ML and DL methods used for detecting depression through social media data. It also suggests a general system design, summarizes popular datasets and approaches, and points out areas that need more research. By focusing on social media platforms, this review helps in understanding how modern technologies can support depression detection. However, it does not include other methods such as graph-based or reinforcement learning approaches, which means its findings may not apply outside the social media context.

IndexTerms -

Depression detection, hybrid machine learning, Deep learning, sentiment analysis, social media, convolution neural network, long short-term memory.

I. INTRODUCTION

Social media has become one of the most common ways for people to share their thoughts and communicate. Many users openly express their emotions and personal struggles on these platforms, including serious issues such as feelings of hopelessness, self-harm, or even harmful intentions. Depression is a well-known mental health disorder and is among the most common psychological illnesses affecting people all over the world. It can be dangerous because it influences both mental and physical health, often leading to serious consequences if left untreated. The level of depression is usually determined by evaluating a person's overall mental condition [1]. Some of the most frequent mental health problems include anxiety, restlessness, sleeping issues, eating disorders, addiction, trauma-related conditions, and stress[2]. The development of **deep learning** has brought major improvements in detecting such conditions. Researchers began using advanced models like **Recurrent Neural Networks (RNNs)** [3],[4],[5] and **Convolutional Neural Networks (CNNs)** [6],[7],[8] to understand the sequence and meaning of words in social media posts. Later, **transformer-based models** such as **BERT** achieved even higher accuracy by better understanding natural language and identifying.[9] In Thailand, the number of people experiencing depression has steadily increased. In 2009, there were about 270 cases per 100,000 people, which rose to 345.1 cases per 100,000 in 2019. [10] By 2023, around 1.5 million people were estimated to suffer from depression according to the two-question screening test (2Q test). Unfortunately, nearly 78% of them did not receive proper treatment or were unaware of their condition.[11] Depression is also a major factor behind suicide. The suicide rate increased from 5.9 cases per 100,000 people in 2015 to 7.94 in 2023, with over 5,000 deaths that year—58% of which were linked to depression [12].

II. LITERATURE REVIEW

A. Sentiment Analysis from Social Network Data

This line of research focuses on creating algorithms that can identify the emotional tone of data shared social media. Barhan and Shakhomirov [13] designed a model that classifies sentiment from "X" data using word extraction methods. Their experiments showed that the **Support Vector Machine (SVM)** algorithm performed better than **Naïve Bayes**, achieving **81% accuracy** and

74% recall. Similarly, Hutto and Gilbert [14] compared multiple algorithms—SVM, Naïve Bayes, and Maximum Entropy—using 4,000 "X" posts. Their study found that **SVM gave the best results with 91% accuracy**. Later, deep learning techniques were tested and achieved around **75% accuracy**, showing an improvement over traditional machine learning approaches such as SVM and Naïve Bayes.

B. Depression Detection from Social Networks

The next group of studies aims to build algorithms capable of identifying signs of depression from the vast amount of data shared on social media platforms. Wang et al. [15] proposed a method to detect depression by analyzing social media activity using sentiment analysis techniques on data from 180 users, achieving **80% accuracy**. Park et al. used the **SVM** model, which provided **70% accuracy**, showing its efficiency in depression detection Jiang et al. [16] studied how speech characteristics relate to depression by analyzing 170 participants (85 diagnosed with depression). Their work examined three speech types—interview, picture description, and reading—as well as three emotional tones (positive, neutral, and negative) to help identify depressive tendencies.

C. Depression Model Development

User profiles and activity on social networks often reveal negative emotions or psychological distress. This area of research focuses on tracking users' posts and identifying depressive patterns using classification techniques like **SVM** and **Naïve Bayes**, which achieved accuracies of 57% and 63% respectively. Zhu et al. [17] developed a system that predicts depression based on internet usage behaviour. The goal was to design a new method for early detection and prevention of depression by analyzing how frequently people use the internet. Their study involved 728 students, collecting both depression test results and online activity data. The classification model effectively distinguished between high and low depression groups, showing that frequent internet use may influence mental health levels.

III. RESEARCH METHODOLOGY

The proposed system is built using the Agile development methodology, integrating multiple technologies such as Python, OpenCV, HTML, CSS, Bootstrap, and JavaScript. The main components of the system include:

- **Login and Dashboard:** Handle user authentication and data entry.
- **Face Detection Module:** Uses the **Haar Cascade Classifier** to detect faces.
- **Expression Detection Module:** Employs the **Xception CNN** architecture for facial expression analysis.
- **Speech Recognition Module:** Uses **acoustic feature extraction** for identifying vocal cues.
- **Chatbot Module:** Built using the **ChatterBot Python library** to provide user interaction and guidance.

The **Goldberg Depression Questionnaire** is integrated to collect users' self-reported emotional states.

IV. SYSTEM DESIGN AND ARCHITECTURE

The system uses a multimodal design, meaning it processes data from several sources like text, images and voice. After logging in, users can access a dashboard to upload facial images, fill out questionnaires, or record voice inputs. The system analyzes these inputs through pre-trained machine learning models to calculate a depression score. Depending on the result, the chatbot offers personalized responses such as motivational quotes, entertainment suggestions, or contact details for mental health professionals.
This section explains the overall design of a depression detection system—from collecting raw data to evaluating the model's performance. Figure 1 shows a visual overview of these stages.

A. Data Acquisition

The first step is to gather social media data like posts, comments, pictures, and metadata from platforms such as Twitter, Reddit, Facebook, and Instagram. Data can be obtained in two ways:
Self-Collection: Using APIs (e.g., Twitter API, Reddit API) to directly extract posts and user activity.
Public Datasets: Using already available and labelled datasets, which are helpful for training and evaluating depression detection models.

B. Data Preprocessing

Once data is collected, it must be cleaned and prepared for model training. Preprocessing ensures that the information is consistent and usable. Key steps include:

- **Text Cleaning:** Removing unnecessary elements such as links, special characters, or emojis.
- **Tokenization:** Splitting text into smaller parts (tokens) like words or phrases.
- **Stopword Removal:** Deleting common words (e.g., "is," "the," "in") that don't add much meaning.
- **Normalization:** Standardizing words (e.g., converting "running," "runs," and "ran" into "run") to reduce variation.
- **Image Processing:** Preparing images (resizing, converting to grayscale, etc.) before feeding them into deep learning models.

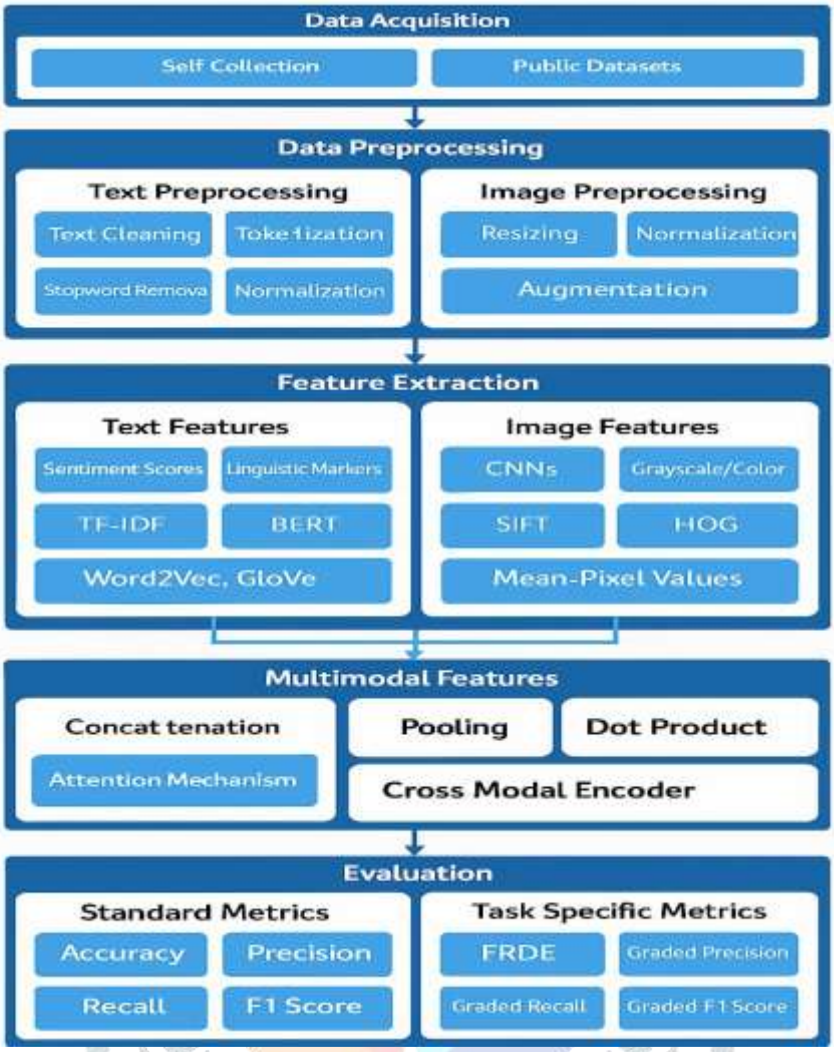

Fig1. System design and architecture

C. Feature Extraction

This step converts the cleaned data into numerical features that models can understand.

- **Text Features:** Include sentiment scores, frequency of emotional words, and linguistic patterns.
- **Image Features:** Extracted using CNNs, grayscale pixel averages, or Histogram of Oriented Gradients (HOG) to capture visual cues.

D. Classification Models

After extracting features, the system uses classification algorithms to detect signs of depression.

Machine Learning Models: Such as SVM, Random Forest (RF), Logistic Regression (LR), and Decision Tree (DT) for text-based classification.

Deep Learning Models: Include RNNs, LSTMs, BERT, RoBERTa for text, and CNNs, vision transformers for image based data. These models can identify complex patterns across different data types.

E. Evaluation

The system's accuracy and performance are measured using several metrics:

- **Common Metrics:** Include Accuracy, Precision, Recall, F1-score, and AUC.
- **Specialized Metrics:** For depression detection, specific measures like ERDE, Graded Precision, Graded Recall, and Graded F1 are used to evaluate how well the model detects depression early and accurately.

V. RESULTS AND DISCUSSION

The Depression Detection System was tested using sample datasets and real-time user inputs. The Haar Cascade Classifier accurately detected facial regions, while the Xception CNN model achieved reliable emotion classification. Voice-based recognition further enhanced prediction accuracy. The integrated chatbot effectively engaged users and provided relevant recommendations. Although the system provides approximate predictions, it serves as a valuable preliminary screening tool for identifying potential depressive symptoms.

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