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Depression Detection System using Hybrid Deep Learning and Social Media Data

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Abstract
Depression is one of the most common mental health disorders, which is increasingly being expressed through online social media platforms. Depression, however, remains untreated and even goes unnoticed. Motivated by the recent advances in affective computing and social media analysis, this paper proposes a depression detection system that combines text, emoji, and image modalities of social media posts using a hybrid machine learning approach. The proposed system builds upon the recent advances in the sentiment pretraining stage and the depression-specific fine-tuning stage. The system employs a multi lingual DistilBERT-based text encoder, along with an emoji aware text preprocessing approach, and an EfficientNetB4-based facial expression model for image analysis. The proposed system combines the power of deep representation learning and metrics based classifiers for detecting sentiment, emotion, and visual affect attributes of the social media posts of the users. Extensive experiments using publicly available sentiment, emotion, and depression datasets have been carried out, which prove the effectiveness of the proposed system. The system achieves good results, with weighted F1-scores greater than 0.87 for multi-class sentiment classification and around 0.90 for binary depression related emotion detection. The results, however, indicate the fea sibility of the proposed system, which is computationally efficient. Index Terms—Depression detection, social media analysis, hybrid machine learning, sentiment analysis, deep learning, DistilBERT, EfficientNet. Index Terms—Depression detection, social media analytics, hybrid machine learning, sentiment analysis, deep learning, DistilBERT, EfficientNet.

1. Introduction
Depression is one of the most important factors that cause disability all over the world. It is also closely linked with quality of life and suicide. [1] The traditional methods that are used to diagnose depression depend on the self-reporting of the patient. However, it is expensive to do this on a large scale and usually occurs after the symptoms have become severe. [2] In the meantime, people are increasingly expressing themselves and their emotions through social media. [3], [4] Agrowing body of research has indicated that the linguistic features and affective and interactional cues in social media posts can be used to detect depression and other mental health conditions. [5]–[7] However, most of the existing methods only make use of text-based features and regard emoji and image features as noise. In addition, most of the methods either make use of traditional machine learning methods with handcrafted features or deep learning methods. However, the strengths of the two methods have not been combined. The Depression Detection System Using Hybrid Machine Learning and Social Media Data is proposed in this paper. The system makes use of the strengths of multiple features in the text, emoji, and image modalities in the context of deep learning and machine learning. stage hybrid pipeline. In Stage 1, the multilingual Distil BERT model is pre-trained on large-scale sentiment corpora to learn strong representations of language in different languages and domains. [20], [23] In Stage 2, the pre-trained

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text encoder is fine-tuned for depression-related emotion detection using a mental health dataset, and an image classifier based on the EfficientNetB4 model is trained to classify images based on facial expressions using emotion-labelled face datasets. [28], [30], [31] Compared to similar work such as D2X, [4], which employs support vector machines and random forest algorithms based on aggregated feature sets of individual tweets, our approach differs in the following ways

- We make use of pre-trained deep transformer models for multilingual text understanding.
- We include the representation of emoji and emotion labels in the text understanding pipeline.
- We extend the text screening approach with an image classifier based on facial expressions specific to depressive and non-depressive states. The contributions of the paper are
- We present a novel hybrid two-stage approach combining large-scale sentiment pretraining and depression-specific fine-tuning of social media text data.
- We also present an emoji-aware text preprocessing pipeline and an EfficientNetB4-based emotion classifier for images, which are unified in a risk scoring framework.
- We evaluate our approach comprehensively using different datasets and show competitive and superior performance in terms of accuracy and F1-score while keeping computational costs manageable.

2. Literature Review

Researches in the area of depression analysis in social networks can be categorized into three areas: sentiment analysis, depression risk detection, and mental health prediction models.Sentiment Analysis in Social Media Research in sen timent analysis in social media began with traditional ma chine learning approaches using n-gram features and lexicon-based methods to classify social media user posts into three categories: positive, negative, and neutral sentiments. The initial studies in sentiment analysis in social media used traditional machine learning approaches with n-gram features and lexicon-based methods to classify social media user posts into three categories: positive, negative, and neutral sentiments. [?], [8], [9]. Another study by Barhan and Shakhomirov used n-gram features and emoticons to classify tweet sentiments and concluded that SVM performs better than Na¨ıve Bayes in classifying tweet sentiments. [8]. Hutto and Gilbert also proposed VADER, which is optimized for social media sentiment analysis and is based on rules. Other studies also used deep learning methods, such as convolutional neural networks and recurrent neural networks, to classify tweet sentiments and concluded that these methods perform better in other languages, such as Thai. Sentiment analysis is also used to analyze the moods and emotions of people in society. Depression Detection Using social media Several studies have also been done in the area of depression detection using social media data. Wang et al. used sentiment features of microblog messages to classify depressed and non-depressed people with an accuracy of 80 Deep learning-based methods have also been explored. Orabi et al. have compared CNN and RNN for depression detection from Twitter, where CNN outperforms RNN on public datasets. [6] Khafaga et al. proposed a deep learning-based model that achieves near perfect accuracy for depression detection from tweet texts. [7] Other than text, speech, facial expressions, and images posted on social media platforms like Instagram are also considered as predictive features for depression. [15], [16], [17], [18] Hybrid and Multi-Modal Models Hybrid models that incorporate various features and learning algorithms have also shown promising results for mental health prediction. Reece et al. proposed a random forest-based model for predicting the onset of mental illness from Twitter, where the authors observed that incorporating various features enhances the predictive accuracy. [3] Sun et al. proposed a hybrid deep learning model that combines CNN, LSTM, and Markov chain Monte Carlo for emotional transitions in conversations. [19] More recently, Angskun et al. proposed a hybrid deep learning-based model D2X that combines features from text, emoticon, and images, and uses SVM-based recursive feature elimination and random forest modeling for depression detection. [4] pre-trained language models like BERT and its variants have shown significant improvements in natural language understanding and have been applied for various mental healthcare applications. [20]– [24] Ji et al. proposed a language model called MentalBERT, where the model is fine-tuned for mental health-related texts. However, there are few works that incorporate general sentiment pre-training, depression-specific emotion mapping, and multi-modal fusion within a single model. Our work is also closely related to D2X [4] but with three main differences: (i) we use a multilingual DistilBERT encoder with large-scale sentiment pretraining, (ii) we use an emotion mapping from GoEmotions to depression-related classes, and (iii) we use a powerful EfficientNet classifier for facial emotion detection for image posts, using an ensemble-style risk scoring mechanism.

3. Methodology

In this part, we will describe the overall methodology used in the suggested system. The pipeline consists of two main branches that operate with texts/emojis and images, respectively. The final output is produced by combining predictions of the two branches on a decision level.

3.1. Problem definition

The task is to determine the depression risk of a certain person based on a set of their social media posts in the time window. The problem formulation is as follows:

- Multi-class classification of post sentiments/feelings into sad, happy, anger, fear, and neutral classes.
- Binary classification of whether a particular post/user is related to depression or not.We denote x(t), e(t) as textual and emoji parts of the social media post made at the time t. Similarly, v(t) is the corresponding image. The algorithm learns the following mappings :ftext:(x(t),e(t))→y(t)text, fimg : v(t) → y(t)img

These values are combined over the user to estimate the overall depression risk score $r(u) \in [0,1]$ and binary depression classification $\hat{y}(u) \in \{0,1\}$ for a given user u.

3.2.Data sources

In order to construct our system we use several data sources with the following characteristics:

- Sentiment140: contains approximately 400,000 tweets labeled for binary sentiment, remapped to classes {0,1};
- Twitter Sentiment Dataset: contains 162,969 tweets with labels negative, neutral, and positive, remapped to classes {0,1,2};
- Hinglish Sentiment Dataset: dataset with 2,721 code-mixed (Hindi-English) tweets for robust sentiment analysis across languages;
- GoEmotions: a collection of Reddit posts with 54,263 posts annotated with 27 emotions labels. We will group emotions into five broad classes: sadness, anger, fear, joy, neutral;
- Mental Health Dataset: dataset containing labeled statements related to various mental conditions like depression or anxiety.Image datasets we will use
- AffectNet: large dataset of face expression with different emotions labeled. We take images with “sad” or “happy/normal” labels;
- FER2013: large scale dataset of facial emotions; we will map emotions into depressive and non-depressive categories.

3.3.Overall Pipeline

In the process, we will implement our pipeline in two stages

- Stage1: Generic Sentiment Pretraining (Text):In this step, we train the multilingual DistilBERT model on combined sentiment data sources to generate general representations for the language:merge all three sentiment datasets into one, remove duplicates, obtain ~563K samples;preprocess the text data: lower case conversion, URL removal, punctuation and normalizations of whitespaces;tokenize text data using distilbert-base-multilingual-cased with max

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seq length of 196;train three-class classifier using cross entropy loss, Adam and early stopping using HuggingFace's Trainer.

- Stage 2: Emotion and Depression Fine-Tuning (Text): We will continue training our pretrained DistilBERT model on emotions and depression-related texts.map emotions in GoEmotions to broader groups: sadness, anger, fear, joy, neutral;train five-class classifier by replacing only the output layer of pretrained DistilBERT;fine-tune this network on mental health texts to learn depression classification by training the new classifier head.
- Image-Based Branch:This branch consists of two steps:collect depressive and non-depressive images from AffectNet and FER2013. Approximately, 15,842 images. balance this dataset using under sampling technique; apply preprocessing including resizing to 224 × 224 and basic augmentations like horizontal flip;use EfficientNetB4 pretrained on ImageNet as a base and freeze all but last layers. Then, we add Dense output layer with Batch Norm and Dropout.apply focal loss for class imbalances optimization, Adam optimizer

At inference time, the following is performed:

- text depression probability estimation for each post/user is done using the Stage 2 classification head, along with emotions probabilities such as sadness and fear;
- image-based predictions for each post is done via average predictions of three independent EfficientNetB4 networks.Each post's probability of being depressive is estimated as:

$$r(t)=\alpha p(t)text+(1-\alpha)p(t)img$$

Where p(t)text and p(t)img denote the prediction probabilities of depression on each modality, respectively, and $\alpha \in [0,1]$.

The depression probability of the user can be estimated as the average over the post-level probabilities:

$$r(u) = (1/Tu)\ \Sigma\ r(t).$$

And finally, the user classification is performed as:
$\hat{y}(u)=1, if r(u)\geq\tau, 0 otherwise,$
where the threshold τ is chosen on validation set for maximizing F1-score.

4. System Architecture

This part of the essay outlines the system architecture starting from data collection to risk score generation.

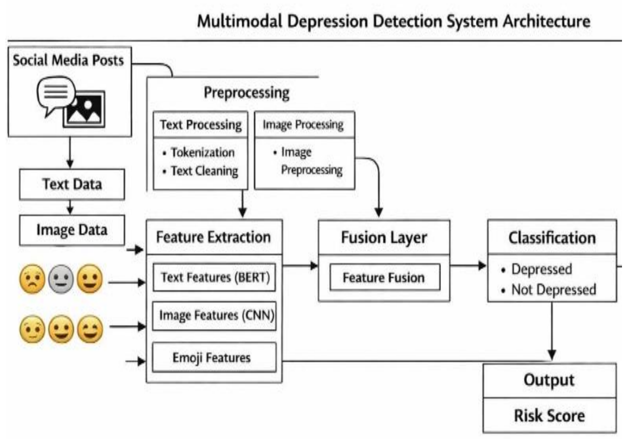

Figure 1 High-Level System Architecture of The Proposed Depression Detection System.

4.1. High-Level Design

Figure 1 shows the high-level architecture of the designed solution.

Key modules include the following:

• Data Collector: Collects social media messages in form of text, emojis, and images through the use of API interfaces and keeps them stored in a secured database.

• Preprocessing and Feature Generation: Performs cleaning, tokenization of text, conversion of emojis into sentiment/emotion scores, image resizing, and normalizing.

• Text Sentiment and Emotion Module: Applies DistilBERT algorithms (Stage 1 & Stage 2) for sentiment and depression assessment.

• Image Emotion Detection Module: Applies an EfficientNet algorithm for detecting depressive face expressions.

• Decision Engine: Consolidates both modules'

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results to determine users' risks.

• Interface Layer: Offers end points for individual user analysis and also dashboard-style analytics for stakeholder consumption.

4.2. Text and Emoji Processing

The processing flow for text entails:

Data Cleaning: Removal of URLs, mentions, and hashtags, while preserving the meaning of the post.Normalization of the post via conversion to consistent format, removal of extra spaces, while leaving alphanumeric characters with emojis intact.

Emojis handling: Conversion of emojis into readable textual description using emoji libraries to facilitate emotional understanding of posts by the model.Sentiment score can be attached to emojis if required by means of available resources for sentiment ranking of emojis.

Tokenization: Multilingual DistilBERT tokenizer is employed for tokenizing preprocessed text with sequence truncation or padding up to 196 tokens long.

4.3. Image Processing

Processing flow of the image includes:

- Loading each image in BGR color space, converting it to RGB, resizing it to 224x224, and normalization based on EfficientNet preprocessing requirements.
- Training-time data augmentation is achieved via random horizontal image flipping.
- Images are converted to tensors and processed through EfficientNetB4 with global average pooling, and two dense layers including dropout.

4.4. Deployment Considerations

The microservices-oriented architecture is assumed for deployment purposes, including:

- Text Service that processes single posts through Stage2DistilBERT.
- Image Service that uses Ensemble of EfficientNetB4.
- Backend Service that integrates results of models' analysis and stores user-level risk profiles.

5. Implementation Details

This section discusses the most important parts of the implementation pipeline in both branches.

5.1. Text Branch: Stage 1 Sentiment Pretraining

The first stage is based on distilbert-base-multilingual-cased model, utilizing Hugging Face Transformers and PyTorch library:

- Data: Sentiment140, Twitter Sentiment Dataset and Hinglish data is combined, duplicates are filtered out, resulting in a dataset containing 563,429 samples belonging to 3 classes.Train/ Test split: 90%/10% split by labels stratification.
- Hyperparameters:Number of epochs: 3 Batch size: 16 (both training and evaluation phases)
- Learning rate: 1.5x10-5Weight decay: 0.01 Model is evaluated and performance metrics are computed each epoch, the best performing model based on validation loss is saved
- Evaluation metrics: accuracy and weighted F1-score are calculated using sklearn default methods

5.2. Text Branch: Stage 2 Emotion and Depression Detection

5.2.1. For emotion detection task:

- Training/dev/test splits of GoEmotions data are loaded and concatenated into 54,263 samples
- 27 emotions from the original dataset, as well as the category Neutral, is mapped to 5 emotions (sadness, anger, fear, joy, neutral)
- Classification head with number of categories 5 is added on top of the pre-trained on Stage 1 DistilBERT encoder using the same set of hyperparameters as above (number of epochs: 3; batch size: 16; learning rate: 1.5x10-5)

5.2.2. For depression detection task:

- Specialized data comprising samples either belonging to anxiety/depression category or not
- Preprocessing steps stopwords removal, text lowercasing
- The model is built on top of previously created Stages 1&2 models with

additional 2-classes classification head.

5.3. Image Branch: EfficientNetB4 Model Ensemble

The second branch of the system uses Tensorflow and Keras libraries:

- Data: Images labeled with AffectNet/FER2013 labels are loaded
- Data balancing: undersampling of the majority class results in ~15,842 images overall
- Train/val split: 80%/20% by labels stratification
- Network architecture: EfficientNetB4 pretrained on ImageNet; head not present yet.
- Final Head: Global Average Pooling, then Dense layer of 512 units with ReLU activation, Batch Normalization, dense layer of 128 units with ReLU activation, Batch Normalization, two Dropout layers with dropout probabilities of 0.6 and 0.4 respectively, and finally, dense layer with 1 unit with Sigmoid activation.
- Loss Function & Optimizer: Focal Loss with $\gamma = 2$, $\alpha = 0.25$, Adam with a base learning rate of $1 \times 10-4$
- Training: The model is trained for 50 epochs with early stopping and checkpoints that help retain the best performing model according to the validation loss.
- Model Ensemble: Three models are trained with different random states with varying learning rates and averaged in the inference phase.
- Grad-CAM visualizations can be used for qualitative analysis of which parts of the face are impacting the prediction process the most.

6. Results And Evaluation

6.1. Branch Performance in Text Branch

In the combined sentiment dataset in Stage 1,the DistilBERT modelreached:

- Accuracy≈0.87
- Weighted F1-score≈0.87 with class F1

scores at about 0.85 for negative, 0.96 forneutral and 0.86 for positive sentiments.In the case of the five-class emotions mapping using the Go Emotions training dataset in Stage 2, the trained modelreached:

- Validation accuracy greater than 0.86
- Weighted F1-score greater than 0.86

meaning the more coarsely mapped emotions are stilldistinguishable and useful for depression mapping further on.

In the mental health detection task, the two-class classifier
reached:

- Accuracy≈0.90
- Weighted F1-score around 0.90

6.2.Confusion Matrix Analysis

The performance of the depression detection system will be assessed using a confusion matrix as presented in Fig. X below. It shows the classification accuracy of the system for two classes: 'non-depressed' (class 0) and 'depressed' (class 1). From the confusion matrix, it can be seen that the model correctly predicted 12734 cases as being non-depressed (True Negatives) and 14566 cases as being depressed (True Positives). At the same time, 454 cases were predicted to belong to the depressed category while they actually belonged to the 'non-depressed' class (False Positives), while 538 cases of patients suffering from depression were predicted to not be depressed (False Negatives).The performance of the model indicates its excellent capabilities of detecting patients with depression. This is clearly visible from the low number of False Negatives, which is extremely important for a depression detection system because the consequences of the incorrect prediction can be quite serious. Relatively high False Positive values mean that the system has some tendency to over-predict the depressed patients, which may be accepted for healthcare application of such kind where fast reaction is crucial.

Table 1 Representative Results Of Text and Image Models On Validation Sets

Model	Accuracy	Precision	Recall	F1-score
Stage 1 Sentiment	0.87	0.87	0.87	0.87
Stage 2 Emotion	0.86	0.86	0.86	0.86
Depression Model Binary	0.90	0.90	0.90	0.90
Image Ensemble	0.90	0.83	0.99	0.90

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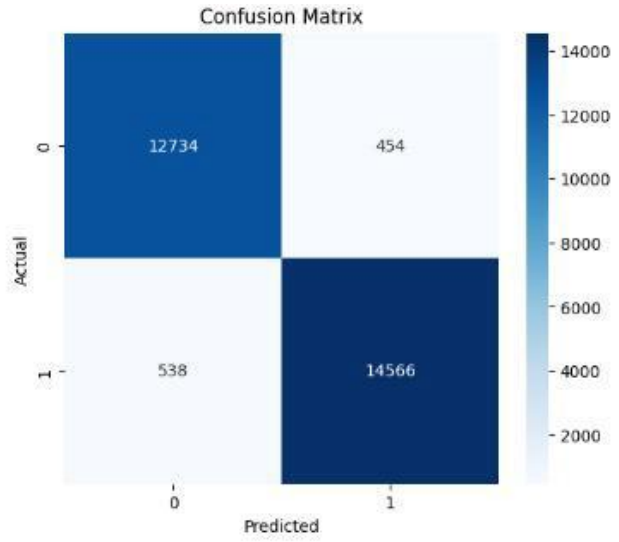

Figure 2 **Confusion Matrix**

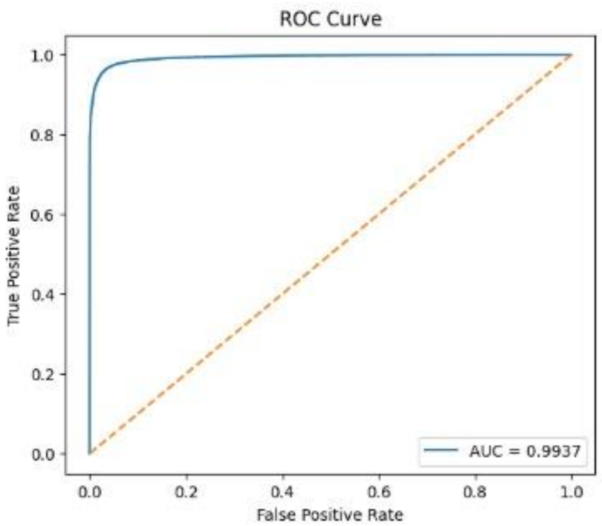

Figure 3 **AUC – ROC CURVE**

Performance Results for the Image Branch

6.3.EfficientNetB4Ensemble

- Validation accuracies above 0.93 and F1-scores closeto0.94 were obtained for each independent classifier on the balanced validation dataset.
- The ensemble obtained the following scores:

  Accuracy ~0.90
  Precision ~0.83
  Recall ~0.99
  F1-score~0.90
  On the validation dataset.

A high recall score implies that the ensemble is unlikely to miss any positive samples, which is advantageous for screening tasks.

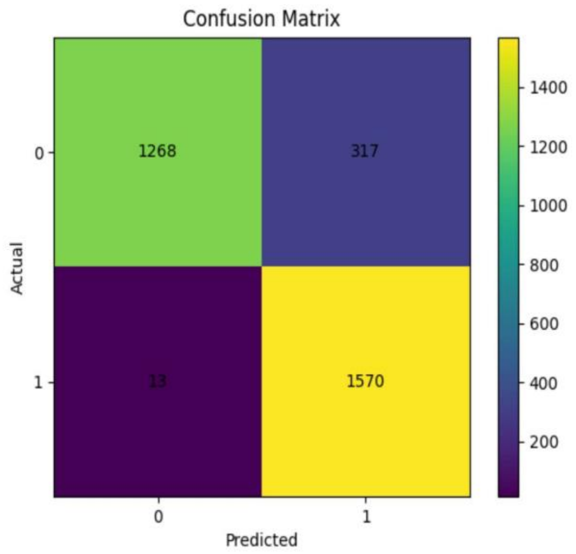

Figure 4 **Confusion Matrix For Images**

6.4.Hybrid Aggregation & Thresholding

In our search for methods of fusion, various risk thresholds τ were considered on a validation dataset. It is observed that the optimal threshold in the case of the image branch is approximately at τ = 0.50, with F1-scores greater than 0.94. As far as the text branch is concerned, the range of optimal thresholds was [0.4,0.6]. In the hybrid approach, the value of α ranged from 0.6 to 0.7, indicating slight preference towards the text modality due to a larger number of posts.Table 1 depicts selected performance measures of each part[10].

6.5.Computational Efficiency

The text branch training process employed a GPU-acceleratedenvironment, batch size 16, which took several hours for both Stage 1 and Stage 2 together. The inference time for a single post would only need asingle pass through Distil BERT, and it is possible to achieve close-to-real-time analysis. Training the image branch for the Efficient Net ensembletook more time owing to its bulky architecture but could still be done on a single GPU. Inference using the Efficient Net ensemble on a single image is efficient and fast, considering that the network would take tens of milliseconds for processing an input size of 224 x

224 pixels [11].

7. Discussion

The findings show that the integration of pretraining on large corpora of sentiments with fine-tuning on emotional and mental health-related issues related to depression leads to accurate results. Stage 1 DistilBERT demonstrates excellent language representations that can easily be adapted for subsequent emotion and depression-related tasks, especially since social media language is highly noisy and diverse linguistically. The inclusion of a vision-based EfficientNet ensemble [12] will complement the text branch in detecting any nonverbal cues of affect such as facial expressions that could possibly indicate depressed affect even if the language is not indicative. The advantage of the image branch, with its high recall rate, is its ability to help avoid false negatives in risk assessment. However, visual cues bring up ethical concerns, which should be addressed in terms of informed consent and on-device deployment. The hybrid aggregator model is quite flexible as well since the weights α and thresholds τ may be tuned according to the desired point of operation depending on what is more important sensitivity or specificity.In case of a high risk scenario, a lower threshold could prove useful to maximize recall.Compared to the conventional hybrid machine learning systems such as D2X [4] that depend on counting the tweets, aggregating their sentiment scores using SVM-RFE feature selection, and classifying the result via random forests, our solution utilizes deep [13] contextual encoders able to understand nuances, code mixing, and emojis. Nonetheless, the model retains the interpretability by including groups of emotions and Grad-CAMs, which means that it could be effectively used to augment human clinical decision-making [14].

8. Future Work

Despite promising results achieved by the described multi-modal approach to depression detection, there are still many areas that can be addressed to improve the model. First of all, efforts should be put into making this framework scalable for web or mobile application deployment and continuous real-time monitoring of user behavior. It would also be beneficial to integrate even larger and more diverse datasets that include more people with different cultural backgrounds and speak various languages to make the model more generalized. Furthermore, other data modalities like audio and video recordings can be included in the model as well to improve emotional representation and increase prediction accuracy. Finally, the used weighted averaging of different modalities can be substituted by more advanced approaches like attention-based models and deep fusion methods. As a final point, new architectures based on state-of-the-art models for image and text classification (such as Vision Transformers for images and transformer-based text processing) should also be tried.

Conclusion

The proposed model has been introduced in this research paperas a hybrid depression detection system based on two different streams of information sources: text, emojis, and images from social media networks. The system consists of a multilingual DistilBERT text encoder pretrained using large-scale sentiment datasets and fine-tuned using emotion and mental health datasets and an EfficientNetB4 model to detect depressive facial expressions. Experimental findings show that both parts achieve high accuracy and F1 scores, and combining these two parts leads to accurate depression risk assessment. Future research plans to implement:

- other modalities, including behavioural features and temporal analysis
- specialized language models such as MentalBERT and training on mental health datasets;
- extension to estimate the level of severity of depression symptoms, not only the risk of developing depression.
- a user study conducted by experts and individuals suffering from depression.

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