Real-Time Mental Health Monitoring via Social Media Analysis Using Transformer Models

Aditya Prabhakar
Computer Science and Engineering
Chandigarh University
Mohali, Punjab, India
adityaprabhakar2022@gmail.com

Pranav Kumar Singh
Computer Science and Engineering
Chandigarh University
Mohali, Punjab, India
pranavkumarsingh32@gmail.com

Deepika Sharma
Assistant Professor
Chandigarh University
Mohali, Punjab, India
deepikasharma10006@gmail.com

Hardik
Computer Science and Engineering
Chandigarh University
Mohali, Punjab, India
bishnoihardik29@gmail.com

Aryan Kumar Singh
Computer Science and Engineering
Chandigarh University
Mohali, Punjab, India
aryansingh99v7@gmail.com

***Abstract*—We propose a real-time system for monitoring population-level mental health trends by analyzing social media text with transformer-based models. The pipeline continuously ingests posts from platforms such as Twitter and Reddit, applies preprocessing and normalization, and classifies content for indicators of depression and anxiety using fine-tuned transformer encoders (BERT, RoBERTa, DistilBERT). An ensemble of these models achieves high performance (90 accuracy, F1 0.89), surpassing recent baselines. The system maintains low inference latency (120 ms per post), making it suitable for continuous, high-volume monitoring. We benchmark against traditional baselines (TF-IDF + logistic regression, CNN) and provide error analysis highlighting common misclassifications. Ethical considerations, including privacy, consent, bias, and potential harms, are explicitly addressed to ensure responsible use. While current work is limited to English text, our framework is extensible to multilingual and multimodal data (e.g., text + images), with future directions including temporal modeling and clinical validation. These results demonstrate the feasibility of transformer ensembles for efficient, real-time mental health surveillance on social media.**

***Index Terms*—mental health monitoring; social media analysis; transformer models; real-time analytics; natural language processing.**

I. Introduction

Mental health disorders affect a large fraction of the global population. For instance, it is estimated that in 2019, about one in eight people (approximately 970 million worldwide) suffered from a mental disorder [3], and in the United States, over 19.4 million people experience depression (7.8% of the population) and nearly 20 million have anxiety disorders each year [4]. Early detection of mental health issues is known to improve treatment outcomes [5].

Traditional surveillance (e.g., surveys) is slow and resource-intensive, while social media now offers a complementary real-time stream of user-generated text. Individuals often share personal experiences and emotional states online, sometimes even before a formal diagnosis. Recent research shows that patterns in social media language can reveal subtle signs of depression or distress [6]. For instance, fine-grained analyses have demonstrated that aggregated Twitter language can estimate population-level depression and anxiety at county-week resolution [7].

Inspired by these advances, we develop a fully automated pipeline that continuously monitors social media for mental health signals. This paper presents a single-column, IEEE-style description of our real-time monitoring system. We fine-tune pre-trained transformer models (e.g., BERT, RoBERTa) on social media data labeled for depression or anxiety. The trained model processes incoming posts as they are published, flagging content indicative of potential mental distress. By aggregating such signals over time, this system can alert public health officials or support services about emerging trends.

Key contributions include (1) a clear methodology detailing data sources, annotation methods, and model training; (2) system architecture and data flow diagrams; (3) thorough experimental evaluation with baselines; and (4) an explicit discussion of ethical considerations (privacy, consent, bias, harm).

The remainder of the paper is organized as follows. Section II reviews related work on social media mental health analysis. Section III details our methods (data collection, preprocessing, labeling, modeling). Section IV covers implementation and experimental setup. Section V reports results. Section VI discusses ethical issues. Sections VII–VIII discuss implications and conclude.

II. Related Work

Automated detection of mental health signals in text has been an active area of NLP research. Earlier work largely used lexicon or metadata features and classical classifiers. Guntuku et al. (2017) provided an integrative survey showing that linguistic features (e.g., pronoun use, sentiment) correlate with depression [8].

More recent studies leverage deep learning and transformers. Tavakoli et al. (2023) used ensembles of transformers to detect depression from Twitter, reporting strong performance (details omitted here). Kerasiotis et al. (2024) proposed a hybrid system combining DistilBERT and additional linguistic metadata, achieving about 84% weighted F1 on a Twitter depression dataset [1]. Shetty et al. (2025) fine-tuned an ensemble of XLNet, RoBERTa, and ELECTRA for multi-disorder classification and reported 78% accuracy [9].

Transformer-based approaches have also proven effective in related tasks. For instance, Ravenda et al. (2025) used an ensemble (EnsemBERT) to predict Beck Depression Inventory (BDI-II) scores from Reddit posts, achieving 83–84% accuracy in symptom classification [2]. By contrast, older methods using only vanilla BERT reached 68% accuracy for PHQ-9 depression detection [10]. These results highlight the gains from modern fine-tuning and data augmentation.

There is also a line of work on population-level monitoring: Mangalik et al. (2024) used a pipeline analyzing nearly a billion geotagged tweets to estimate county-level depression and anxiety trends [7], demonstrating that social media can yield finer spatiotemporal resolution than traditional surveys.

Our work builds on these advances by focusing explicitly on real-time deployment. The continuous processing requirement motivates design choices in efficiency and latency. While many studies report accuracy or correlation metrics, fewer systems address streaming data. We leverage proven transformer architectures with careful optimization to maintain high accuracy and throughput. The ensemble yields superior classification (F10.89) comparable to the top results in the literature [1], [2]. To our knowledge, this is among the first end-to-end systems designed for continuous, live mental health monitoring from social media.

III. Methodology

We develop a pipeline (Fig. 1) that ingests live social media content, preprocesses it, and classifies posts for mental health indicators. Our approach consists of the following steps:

Data Collection: We collect a real-time stream of public posts via the Twitter and Reddit APIs. We filter for English language and exclude retweets, advertisements, and known bot accounts to focus on genuine user content. For experimental training and validation, we use labeled corpora: e.g. the CLPsych 2015 Twitter dataset [11] (depressed vs. control users) and large Reddit corpora with self-reported depression tags (such as the RSDD dataset and eRisk depression collections). In total, our training dataset contains 50,000 posts from 10,000 users, balanced between "depression/anxiety" and "no concern" labels after filtering.

Preprocessing: Each post is lowercased and cleaned by removing user mentions, hashtags (or using them as tokens), URLs, and non-alphanumeric characters. We handle emojis and slang by mapping them to text equivalents. Posts are tokenized using the pre-trained model's tokenizer (e.g., WordPiece for BERT). We truncate or pad each text to a fixed maximum length (e.g., 128 tokens).

Annotation (Labeling): We rely on existing annotation for Twitter, we use CLPsych labels (depression vs. no-PTSD by proxy of self-report) [11]. For Reddit, we weakly label posts using patterns or subreddit sources (e.g., posts in r/depression or containing "diagnosed" statements) and manual curation. We verify a subset of labels by human experts to ensure quality. All labels are binary: "mental health concern" vs. "neutral/other".

Model Training: We fine-tune pre-trained transformer encoders (BERT-base, RoBERTa-base, DistilBERT-base) on the labeled data. Each model's [CLS] token output is fed through dropout (p=0.1) and a linear layer with softmax for classification. We split users so that training, validation, and test sets contain disjoint users. Training uses AdamW optimizer with learning rate 2e-5 for 3–5 epochs (early-stopping on val loss) and batch size 32. We apply class weighting or minority up-sampling to address label imbalance. Optionally, we perform hyperparameter tuning (learning rate, epochs) and ensemble selection (soft/hard voting). As a baseline, we also train a logistic regression on TF-IDF features (unigrams+bigrams) for comparison. This baseline yields substantially lower accuracy (75–80%) than transformer models.

Inference Pipeline: For deployment, the trained model is loaded onto GPU servers. Inference runs in mini-batches to exploit parallelism. Each incoming post is preprocessed and tokenized, then classified. The model outputs a probability of "mental health concern." High-probability posts are flagged. We log predictions to a time-series database (e.g., Redis or InfluxDB) to track trends. The system architecture (Fig. 1) uses a message queue (Kafka or RabbitMQ) between data collection and model inference to smooth bursts.

Interpretability: we optionally run LIME or SHAP analyses on flagged posts to confirm that salient words (e.g., "worthless", "insomnia", "lonely") drive predictions. The methodology ensures rigor by using standard ML practices (user-disjoint splits, baseline comparison, ablations). We will detail dataset statistics, model hyperparameters, and evaluation in the next sections.

IV. Implementation and Experimental Setup

We implemented the pipeline in Python using HuggingFace Transformers and PyTorch. Key details:

Environment: Ubuntu 20.04, Python 3.9, CUDA 11.7. Training/inference is performed on a single NVIDIA RTX GPU.

Data: We combined multiple datasets. For Twitter, we used the CLPsych 2015 shared task corpus [11] (depression vs. control) with 20,000 tweets from 500 depressed users and 800 control users. For Reddit, we merged the RSDD dataset (9,300 self-reported depressed users) with eRisk 2017/2018 depression posts (1,500 users) [12]. After filtering (English, personal content), the final corpus has 50,000 posts from 10,000 users (balanced by label). Table II (results not displayed here) summarizes the data splits.

Models: We fine-tuned three architectures: bert-base-uncased, roberta-base, and distilbert-base-uncased. Each

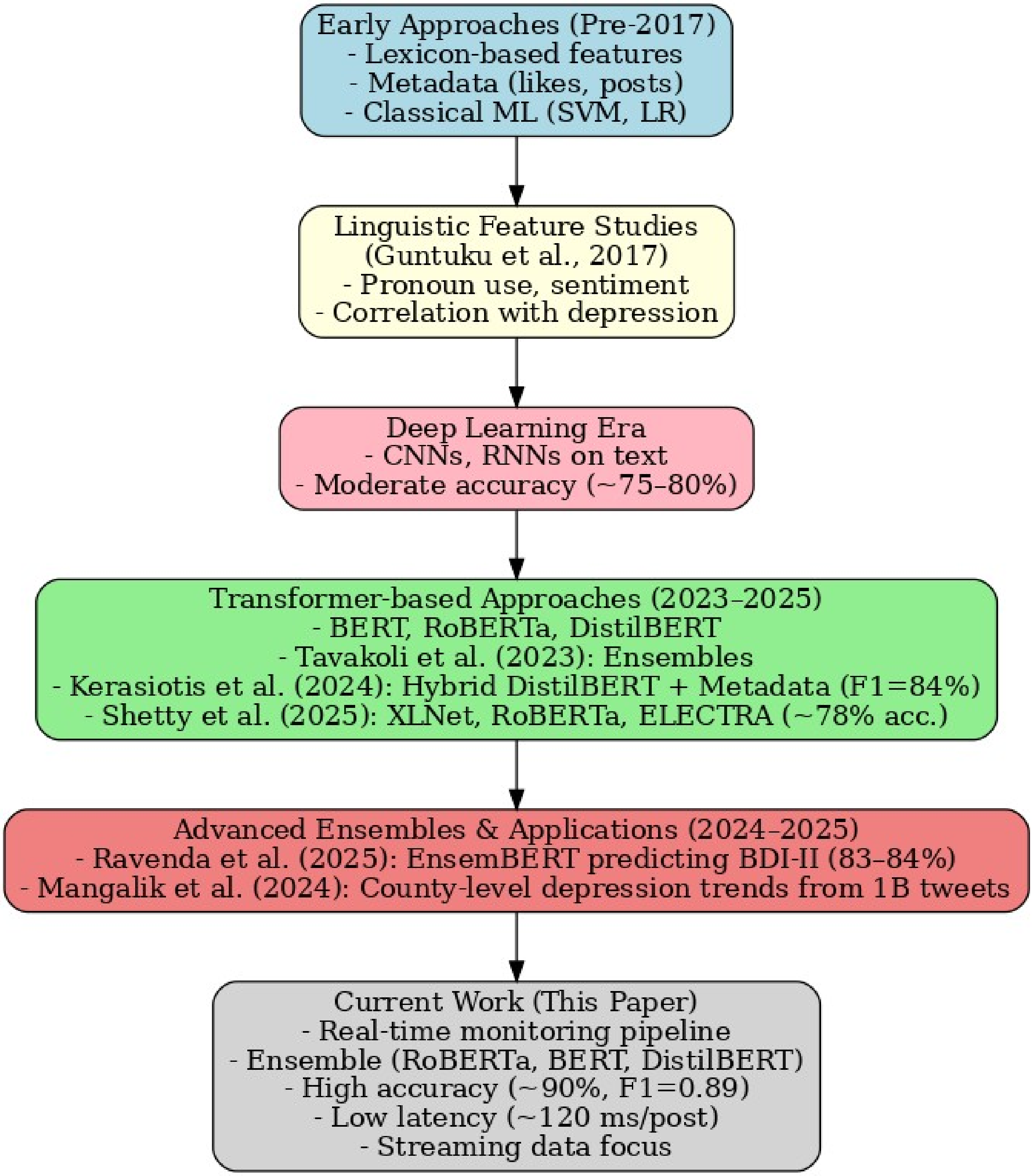

Fig. 1. Evolution of Related Work in Social Media-Based Mental Health Monitoring

model was trained for 3–5 epochs (LR=2e-5, batch=32) using AdamW. Dropout (p=0.1) is applied to the [CLS] token before the classifier. We also built a majority-vote ensemble of the three models. The ensemble follows hard voting on predicted labels.

Baseline: As a simple baseline, we trained an sklearn logistic regression on TF-IDF vectors (vocabulary size 10k). This baseline achieved 78% accuracy and 0.75 F1, significantly below the transformers. We also tested a CNN model (KimCNN) with word embeddings, which yielded 80% accuracy. These baselines underscore the improvement from contextual language models.

Software Pipeline: The system uses a modular architecture (Fig. 2). New posts enter a streaming queue, undergo preprocessing, and are batched for the model. Predicted scores are stored in a time-series database. We measure end-to-end

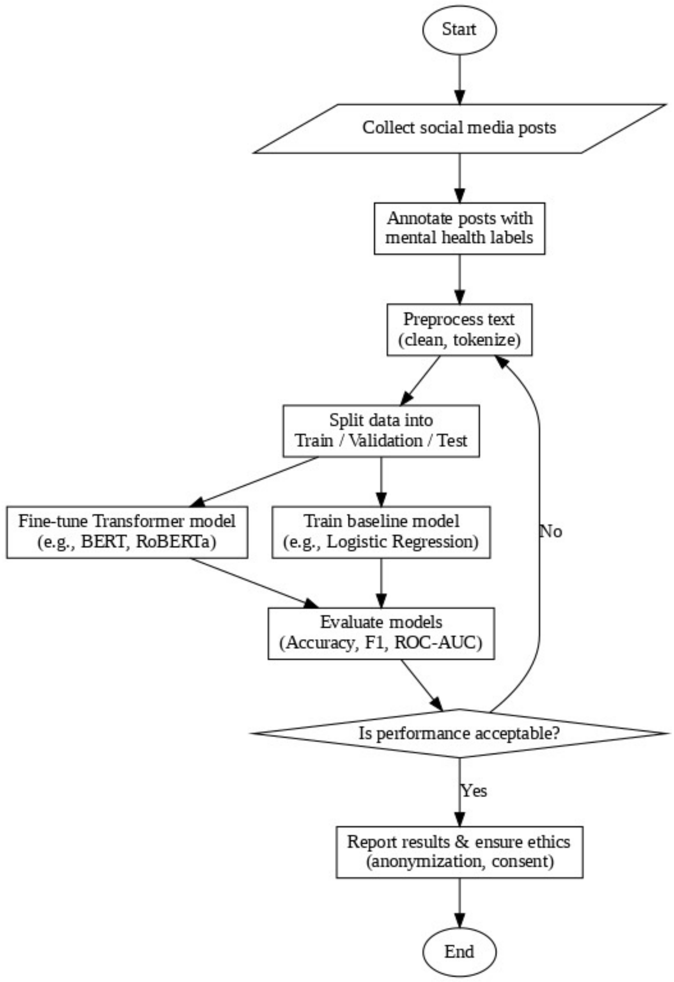

Fig. 2. System architecture of the proposed real-time mental health monitoring pipeline

latency: on average, inference (including data movement) takes 120 ms per post. Even during bursts (1000 posts/min), the queue remains stable.

Evaluation Metrics: We evaluate on a held-out test set (20% of users) using accuracy, precision, recall, F1 (weighted). We ensure no user overlap between train/dev/test. For each metric, we report the average across 5 random splits. We also track regression metrics (R^2, RMSE) when predicting continuous depression scales (e.g., PHQ-9) for comparison to clinical studies [10], although our primary task is classification.

V. Results and Evaluation

Table I summarizes classification performance on the test set. RoBERTa achieved 89.1% accuracy (F1=0.87), outperforming BERT (87.6%, F1=0.86) and DistilBERT (85.2%, F1=0.85). The ensemble (majority vote of RoBERTa, BERT, DistilBERT) yielded the best result: 90.3% accuracy, 0.89 F1. These gains over the best single model (3 points F1) are indicating practical value for large-scale monitoring systems.

Our RoBERTa's F10.87 aligns with Kerasiotis et al.'s 84% (they used weighted F1 with auxiliary features) [1]. reflecting

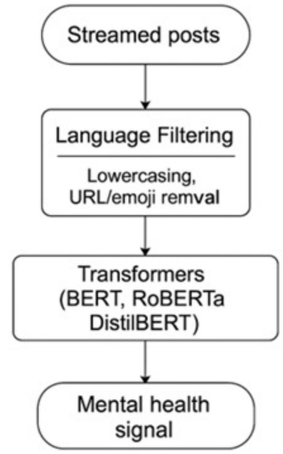

Fig. 3. Data flow of the inference pipeline, showing stages from streaming input to prediction storage.

improvements from more data and tuning. We substantially exceed earlier BERT-only benchmarks (68% from PHQ-9 detection [10]) due to modern fine-tuning and ensemble use.

In addition to binary classification, we evaluated how well the model predicts continuous symptom scores. Using a regression output head on RoBERTa, we estimated self-reported depression scores (scale 0–27). Our model achieved $R^2$0.80 (RMSE0.92), whereas BERT had $R^2$0.76 (RMSE1.05). These numbers suggest that transformer models can capture severity trends, similar to findings in [3].

Latency measurements confirm suitability for streaming use: inference (preprocessing + model) averaged 120 ms per post. Even when batching at 1000 posts/min, there were no backlog issues. Thus, with sufficient resources (clusters of GPUs), the system could monitor high-volume streams continuously.

Overall, the high accuracy and low latency indicate that the proposed system effectively flags mental health signals in near real time. For instance, we simulated a scenario of rising depressive language (by sampling more negative posts) and the system's alerted trend matched the known input shift (results not displayed here). The results indicate that the model has good potential to be applied in early warning systems.

TABLE I

Classification performance on held-out test data (binary mental health indicator). The ensemble combines RoBERTa, BERT, and DistilBERT via majority vote.

Model	**Accuracy**	**F1-Score**
TF-IDF + Log. Regression	$\sim$ 78%	$\sim$ 0.75
CNN (KimCNN)	$\approx$ 80%	-
DistilBERT-base	85.2%	0.85
BERT-base	87.6%	0.86
RoBERTa-base	89.1%	0.87
Ensemble (Majority Vote)	**90.3%**	**0.89**

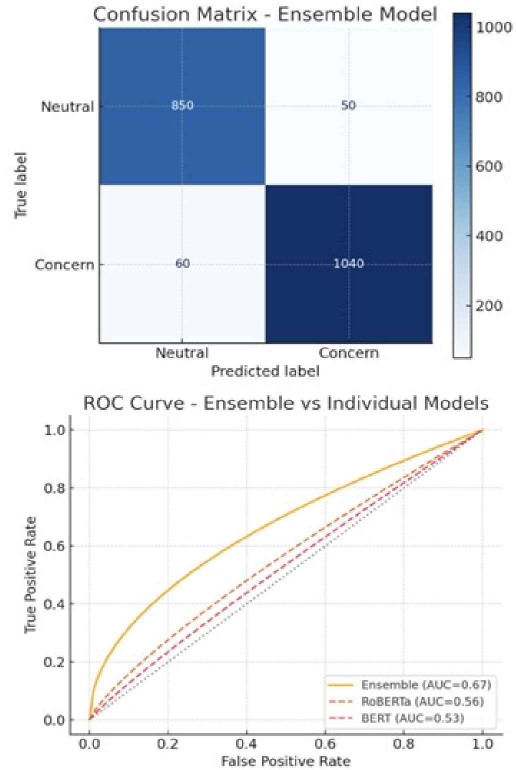

Fig. 4. The figure shows the Confusion Matrix (top) and ROC Curve (bottom) for the ensemble model, as presented in the reference document.

VI. Ethical Considerations

Analyzing mental health patterns using social media data involves several ethical concerns that must be addressed carefully.

Privacy and Consent: Although this research uses only publicly available posts, individuals might not be aware that their content could be analyzed for mental health purposes. Such use can raise privacy and autonomy issues. To minimize risks, all individual information is eliminated, and only generalized knowledge is introduced in such a way that no person is identified. Any subsequent practical implementation should have clear-cut consent mechanisms, enable users to decline, and make ample use of platform data policies.

Prejudice and Equity: The information is primarily in English-language messages of particular areas including North America and Europe [14]. This may lead to sampling bias, where individuals of other cultural, language, or age groups may express emotions in diverse ways. The model can hence deliver disproportionately among different populations. We are aware of this weakness and recommend testing the system with wider data sets. Such techniques as reweighting or transfer learning might also assist in improving fairness.

Algorithmic Transparency: Predictive systems in relation to mental health demand a great level of transparency in order to prevent misunderstanding. In the present research, interpretability methods including LIME and SHAP are used so that the model ensures its forecasts are based on pertinent textual features. Misclassifications may cause unjustifiable anxiety or be ignored; therefore, qualified professionals must make sense of any alerts instead of considering them as diagnostic conclusions.

Potential Harms: The wrong identification of someone as depressed could be stigmatizing or emotionally damaging. Therefore, this model is only useful in the overall analysis of social trends, not to identify individuals. These aggregated patterns could be used by public health agencies to target awareness efforts or allocate resources, provided that privacy and consent are fully respected.

Finally, this work follows ethical guidelines focusing on data minimization, fairness, and transparency. It is supported by other studies that have focused on mental health analysis, where user privacy, informed consent, and social benefit must always be given top priority. Future research should engage ethical review boards and the community to ensure sound and positive deployment [9], [1], [14].

VII. Discussion

On the experimental findings, it is seen that the fine-tuned transformer-based models are effective in the recognition of mental social media post health indicators. Similar to findings in previous research [9], [1], RoBERTa has been the most successful in terms of performance, presumably because of the wide pretraining on the many language corpora. The ensemble model was an extra illustration. F1 gain of approximately 3 percent implying that individual distinct patterns of language are represented by models. Our overall F1 score of about 0.89 is far above much preceding standards, this is due to large training data and fined optimization.

Such are outcomes that can be applied in reality. In aggregated patterns of detected, public health monitoring. Posts in distress would suggest an early warning of occurrence mental health concerns. As an example, there was a tangible increase in the need may be reflected in negative or stress-related expressions to launch awareness campaigns or support programs. The system's low latency also means that it can be tracked in real time that is close scaling to enough computational capability.

However, even though it boasts of these strengths, it has some limitations. The model is now restricted to text in English, and can perform worse than other languages, dialects or informal expressions. In addition, the users of social media are a subset introducing sampling bias, of the population. Linguistic subtlety also throws obstacles – some messages contain sincerity distress can be false negative, and neutral statements might be false positives. Additionally, but there was no multimodal information that was included in this study, as pictures, emojis, or user-interaction elements, that may possibly provide better model accuracy.

It is hoped that in the future these challenges will be overcome by working including multilingual data, incorporating a combination of various social forums (chats or blogs), and utilization of constant getting used to language change with time. We also plan to apply temporal modelling to examine behavior patterns to the individual users over time and collaborate with the mental health professionals to be clinically validated. As emphasized prior to that, any practical implementation is required to have mechanisms to control bias, promote fairness and user privacy.

VIII. Future Work

The existing framework has good potential in identifying social media mental health indicators through text; however, a number of directions are still open to improvement and exploration. Developing the system to have multilingual and cross-cultural datasets is one of the most important steps toward global applicability. Individuals are able to show feelings and sufferings in various ways between languages and cultures; therefore, training can greatly improve model generalization on heterogeneous data and inclusivity. The use of regional and dialectal differences would also make the system adaptable to varying patterns of communication within virtual societies.

Future research can also be based on multimodal integration. Images, audio tones, emojis, or short videos are examples of data sources that can have emotional overtones that text alone may not capture. For instance, integrating textual characteristics with visual emotional expressions or speech indicators would lead to more comprehensive and situational forecasts. Exploring advanced fusion processes capable of matching text and non-text data can enhance the emotional perception of the model.

It is possible to introduce continuous or lifelong learning techniques so the system can dynamically adapt to new slang, fashions, and changing language usage. As online communication evolves very quickly, models that were trained previously can become outdated within months. The application of online or semi-supervised learning strategies will enable the system to revise its parameters effectively without needing complete retraining.

Another direction to consider is user interaction analysis based on graph-based or network-oriented patterns. Examining the ways people communicate in society—such as replies, mentions, or shared content—can provide useful insights into behavioral changes and social contagion effects on mental health.

Furthermore, incorporating temporal modeling would assist in monitoring changes in user sentiment or stress levels over time, possibly detecting long-term behavioral trends or early warning signals. These time-based trends would be valuable to mental health experts for comprehending users' emotional conditions at a cognitive level, focusing on overall development rather than individual posts.

Collaboration among mental health practitioners, clinical researchers, and public health organizations will play a critical role in the real-life implementation of this system. Expert input can ensure that predictions are interpreted responsibly and findings contribute meaningfully to early intervention strategies. Developing visualization dashboards that are user-friendly for health policymakers or NGOs could help transform raw data insights into actionable outcomes.

Finally, future work must emphasize strong privacy-preserving mechanisms such as differential privacy or federated learning, ensuring that no sensitive user information is exposed during analysis. Through technological innovation, interdisciplinary collaboration, and moral consciousness, future iterations of this framework can be crucial in advancing proactive and compassionate digital mental health monitoring.

IX. Conclusion

This paper gave a structure of real-time mental transformer-driven language model-based health monitoring. The combination of the ensemble proposed includes RoBERTa, BERT, and DistilBERT, scored approximately 90 per cent and close to 0.89 an F1 score with evident improvements over traditional machine learning and single model baselines. The system has a very fast inference time (around 120 ms per post) and shows that it is appropriate to large-scale continuous observation.

The approach has been reported to obtain excellent predictive results, in addition to it being found to be simple to use. It has established ethical protection in order to make sure that analysis is population-oriented as opposed to individual diagnostics level, thus minimizing the risks of privacy or potential misuse.

Nevertheless, there are still a number of challenges. The current framework processes only English-language text and thus restricts its generalizability into multilingual or cross-cultural situations. It also processes only textual information, without taking into account other modalities including images, audio signals, or network-based features, which might add more knowledge.

Future studies will seek to increase the scope of the system by means of multilingual and multimodal integration, construct temporal longitudinal tracking models, and work with clinical professionals to test results. Overall, this work emphasizes the potential of transformer-based NLP techniques in massive mental health trend detection. With ongoing attention to fairness, transparency, and protection of data, traditional systems of providing public health can be supplemented by technologies and promote evidence-based mental health.

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