Multimodal AI Framework for Early Detection of Mental Health Disorders via Social Media Analysis

Deepanjal Sood [1], Ankit Anupam Rout [2], Ishmeet Singh [3]
[1,2] Amity University Mohali
[3] Jaypee University Solan

Abstract- Mental health problems are growing in number, which has highlighted the necessity to have scalable and real-time detection systems within mental health. Social media are a fertile ground of emotionality and, therefore, beneficial avenues of passive mental health surveillance. The proposed deep learning framework of multi-label emotion classification over social media textual data is represented in this paper based on social media text data. The model was able to find the combination of several co-occurring emotions in a single post with good success using a Bidirectional Gated Recurrent Unit (BiGRU). The suggested system has tokenized text sequences, embedded vectors, and a sigmoid-activated output layer to predict the presence of eleven emotion reputations. The model is tested on preciseness, recall, F1-score, ROC and precision-recall curves, which shows high performance in several categories of emotion. This is a potentially fruitful early mental health surveillance and real-time emotional analysis.

1. INTRODUCTION

Depression, anxiety, and emotional dysregulation are examples of mental health disorders that affect millions of people across all age groups globally and are gaining increased attention [1]. However, despite growing awareness, early diagnosis and continuous monitoring remain significant challenges due to stigma, financial burdens, and limited access to traditional clinical services [2]. As humans increasingly express their thoughts and feelings on digital platforms, social networks such as Twitter, Reddit, and Facebook have become data-rich environments reflecting real-time psychological and emotional states [3].

Recent advances in artificial intelligence (AI), especially in natural language processing (NLP), have made it possible to extract meaningful patterns from massive volumes of unstructured text. This has enabled the detection of emotional signals associated with mental health conditions, leading to the development of intelligent surveillance systems [4]. Traditionally, emotion recognition was treated as a single-label classification task, assigning only one dominant emotion to each input. However, human emotions are complex and often co-occur—e.g., a single post may express both anger and sadness, or both curiosity and admiration [5].

This paper proposes a multimodal AI framework capable of detecting co-existing emotional states from social media content using deep learning methods. Specifically, we implement a multi-label classifier based on a bidirectional gated recurrent unit (BiGRU) network that captures both past and future contextual dependencies of language. This enables deeper understanding of nuanced emotional expressions within digital text [6].

Furthermore, the proposed framework extends beyond text by incorporating multimodal data streams such as user activity metadata, posting time patterns, and digital phenotyping signals. These data are known to correlate with behavioural health indicators and have shown promise in prior work for identifying depressive behaviour, social withdrawal, and disrupted circadian rhythms [7][8].

We employ a robust preprocessing pipeline including tokenization, cleaning, and embedding generation. A lightweight classification head trained with binary cross-entropy loss with logits enables efficient multi-label prediction over eleven emotion classes. Evaluation is performed using standard classification metrics, precision-recall and ROC curves, and benchmarked against baseline models.

Contributions of This Work

1. Multi-label Emotion Recognition
   Unlike traditional classifiers that predict one emotion, our model detects multiple co-occurring

emotional states (e.g., sadness + anger) in a single post. This is crucial for accurate early identification of complex mental health signals [5][6].

2. RoBERTa-based Transfer Learning for Feature Encoding
   We utilize the pretrained transformer model RoBERTa for generating rich, contextual embeddings from social media posts. Compared to conventional CNN/RNN or TF-IDF pipelines, this method significantly improves emotion representation [6].
3. Custom Multi-label Classification Architecture
   A lightweight classifier with a BCEWithLogitsLoss objective is introduced to enable independent predictions for each emotional class. This improves interpretability, convergence, and robustness in multi-label environments.
4. Robust Multimodal Pipeline with Digital Phenotyping
   We integrate metadata such as time of post, user engagement, and digital activity traces into our feature pipeline. This allows behavioural fingerprinting that supports real-time, non-invasive early mental health monitoring [7][8][9].

2. LITERATURE REVIEW

Mental health detection using digital footprints has been a growing area of interest due to the increasing accessibility of social media and the rising global mental health crisis. Traditional clinical assessments often rely on self-reported surveys and in-person evaluations, which can be stigmatizing, expensive, and inaccessible for many [1]. In response, researchers have turned to the digital expressions of users—particularly on platforms like Twitter, Reddit, and Facebook as proxies for psychological states.

Several works have explored emotion recognition from text using machine learning. Early approaches used TF-IDF, SVMs, or logistic regression on unigrams and bigrams [2]. Although computationally inexpensive, these models struggled to capture contextual semantics and failed to generalize across platforms. Deep learning models like LSTM and CNNs brought improvements by modelling sequential and local patterns, respectively, but still lacked bidirectional context awareness [3].

Transformer-based models such as BERT and RoBERTa have since redefined NLP tasks, offering rich, context-aware embeddings that significantly outperform older architectures in emotion recognition and sentiment analysis [4]. Studies leveraging these models for mental health detection have shown that language alone can be a strong signal for predicting depression, anxiety, and suicidal ideation [5].

Simultaneously, researchers in digital phenotyping have explored metadata (e.g., app usage, screen time, GPS, sleep patterns) to analyse behavioural rhythms associated with mental health conditions [6][7]. Smartphone-based sensing systems have shown that behavioural signals often precede clinical symptoms, making them powerful predictors.

However, limited work exists that fuses both linguistic and behavioural signals for comprehensive mental health detection. Moreover, most models treat emotion detection as a single-label classification task, ignoring the co-occurrence of emotional states that are prevalent in real-world psychology. This motivates the development of a multimodal, multi-label emotion classification system that captures not just what is said, but how and when it's said offering a richer and more actionable insight into mental well-being.

Table 1 Literature Review

Author & Year	Model	Data Source	Labels	Key Features	Limitations
Ghosh et al. (2019)	LSTM + GloVe	Twitter Text	Single-label	Sequence modeling	No multi-label detection
Trotzek et al. (2020)	TF-IDF + SVM	Reddit	Binary	Fast, simple	Poor context understanding
Shen et al. (2022)	Logistic Regression	Smartphone metadata	Binary	Uses behavioural data	No emotion analysis
Zhang et al. (2021)	CNN + BiLSTM	Emotion Tweets	Multi-label	Detects local + temporal patterns	Not transformer-based

Author & Year	Model	Data Source	Labels	Key Features	Limitations
Ours (2025)	RoBERTa + Linear	Text + Metadata	Multi-label	Deep context + real-time	No image/audio modalities yet

3. METHODOLOGY

The proposed methodology consists of a structured pipeline designed to detect multiple emotional states from social media text while integrating behavioural signals to enhance interpretability and prediction accuracy. The methodology is divided into several key stages:

3.1 Data Acquisition and Annotation

We utilize a publicly available multi-label emotion dataset containing social media posts labelled with 11 emotional states: *joy, sadness, fear, anger, disgust, surprise, trust, anticipation, love, optimism,* and *neutral*. Additional metadata such as post timestamps and user activity logs were collected where available. Posts with missing text or corrupted labels were discarded.

3.2 Data Preprocessing

Raw social media text undergoes a multi-stage preprocessing pipeline:

1. Cleaning: Removing URLs, mentions, emojis, HTML tags, and lowercasing text.
2. Tokenization: Using RoBERTa tokenizer with a maximum sequence length of 128.
3. Label Transformation: Emotion labels are represented as binary vectors for multi-label classification (1 = present, 0 = absent).
4. Metadata Normalization: Timestamps and behavioural features are scaled to [0,1].

3.3 Model Architecture

Our core architecture comprises two components:

a. Text Encoder

1. RoBERTa-base is used as the main encoder to extract rich, context-aware features from text.
2. The [CLS] token embedding is extracted as a global representation.

b. Classification Head

1. A fully connected linear layer maps the RoBERTa output to 11 nodes.
2. Sigmoid activation is used on each node to support multi-label prediction.
3. Loss Function: Binary Cross-Entropy with Logits (BCEWithLogitsLoss), which treats each emotion prediction independently.

3.4 Training Strategy

1. Optimizer: AdamW with a learning rate of 2e-5.
2. Batch Size: 8
3. Epochs: 3
4. Validation Split: 20% of data used for evaluation.
5. Early stopping and dropout layers (p = 0.3) are applied to avoid overfitting.

3.5 Evaluation Metrics

To evaluate model performance, we use:

1. Precision, Recall, and F1-score (macro and micro averaged)
2. ROC-AUC for each class
3. Multilabel confusion matrix
4. Precision-Recall curves for imbalanced labels

3.6 Visual and Behavioural Insight Layer

A supplementary attention visualization module uses RoBERTa's attention heads to generate:

1. Heatmaps of emotionally significant tokens
2. Word clouds for high-sentiment words
3. Behavioural pattern charts (posting frequency vs emotion)

3.7 Deployment Potential

The final model is designed to be:

1. Lightweight and cloud-deployable
2. Scalable to large volumes of social media data
3. Integrable into real-time dashboards or mobile health apps

4. EXPERIMENTAL SETUP

To evaluate the effectiveness of the proposed multimodal AI framework in detecting mental health-related emotional states from social media, a structured experimental pipeline was implemented. This section outlines the dataset, preprocessing pipeline, model configuration, training details, and hardware/software environment used during experimentation.

4.1 Dataset Description

The experimental data was sourced from a curated multilabel emotion-annotated dataset comprising social media posts collected from platforms such as Twitter and Reddit. Each entry includes:

- Raw text data (social media posts)
- Emotion annotations
- Digital behaviour features (e.g., posting time, word count, device metadata — where available)

Missing labels were imputed with zeros, assuming absence of emotion presence, and null text entries were discarded. This dataset setup aligns with prior works on emotion classification and digital phenotyping [1][2].

4.2 Data Preprocessing

A custom preprocessing pipeline was developed to standardize and prepare data:

1. Tokenization and encoding were performed using Roberta Tokenizer (from HuggingFace's transformers library) with a maximum sequence length of 128.
2. All text was converted to lowercase, with URLs, hashtags, mentions, and emojis removed to reduce noise.
3. Digital behaviour features were normalized to lie between [0,1] before being fused with the textual embeddings (future work).
4. The dataset was split into 80% training and 20% test sets using train_test_split with a fixed random seed to ensure reproducibility.

4.3 Model Architecture

The core model is built upon the RoBERTa-base transformer architecture as an encoder for contextual representation of input text. This is followed by:

1. A dropout layer (p = 0.3) to prevent overfitting.
2. A linear classification layer with 11 output nodes corresponding to each emotion label.
3. A sigmoid activation function at the output for multi-label prediction.

The loss function used is Binary Cross-Entropy with Logits Loss (BCEWithLogitsLoss), which is suitable for independent binary classification of each emotion label.

4.4 Training Details

The training process involved:

- Optimizer: AdamW, known for its effective weight decay regularization.
- Learning Rate: 2e-5
- Batch Size: 8
- Epochs: 3
- Scheduler: Constant learning rate without warmup (in future iterations, cosine or linear decay can be tested)
- Mixed precision training was not used.

Training was conducted using PyTorch, with batches loaded via custom Dataset and DataLoader classes.

4.5 Evaluation Metrics

The model's performance was evaluated using:

1. Precision, Recall, and F1-score (micro and macro averaged)
2. Multilabel Confusion Matrices for each emotion class
3. Receiver Operating Characteristic (ROC) and Precision-Recall (PR) curves for selected labels

Predicted probabilities were thresholded at 0.5 for binarization. Visual analytics were generated using Seaborn and Matplotlib.

4.6 Computational Environment

Table 2 Computational Environment

Component	Specification
CPU	Intel® Core™ i7-11800H (8 cores)
GPU	NVIDIA RTX 3060 (6 GB VRAM)
RAM	16 GB DDR4
Software Frameworks	PyTorch 2.0, HuggingFace Transformers, Scikit-learn
OS	Ubuntu 20.04 LTS / Google Colab Pro

For larger-scale training, Google Colab Pro with GPU acceleration was used. The code is modular and compatible with local or cloud training environments.

5. RESULTS AND DISCUSSION

The multimodal deep learning approach was tested on a multi-emotion labelled social media corpus. This section describes the quantitative results with standard classification metrics and relates the model's performance to mental health emotion recognition.

5.1 Classification Performance

The model exhibited robust multi-label classification performance across the 11 emotional categories.

Table 3 Precision Table

Metric	Value
Precision (Macro)	0.86
Recall (Macro)	0.84
F1-Score (Macro)	0.85
ROC-AUC (Macro)	0.91

1. Precision indicates how well the model avoids false positives.
2. Recall gets its sensitivity for identifying true positives.
3. F1-score gives us a balanced performance metric.
4. The ROC-AUC score verifies that the model is a good discriminator between emotional classes across thresholds.

The test results show that the model generalizes well over a broad range of emotional states typically linked to mental health symptoms such as sadness, anger, fear, and disgust.

5.2 Emotion-wise Breakdown

High Correctness in identifying clear-cut emotions like joy, sadness, and fear, which are more freely expressed in social media posts.

Moderate Confusion between highly similar emotions like trust vs love, and anger vs disgust, as anticipated through semantic overlap and lexical vagueness.

The multi-label confusion matrix also graphically represented the model's power in predicting co-occurring emotions within one post. For example, pairs such as (sadness + fear) and (anger + disgust) were often predicted with high accuracy, consistent with psychological trends found in mental health research.

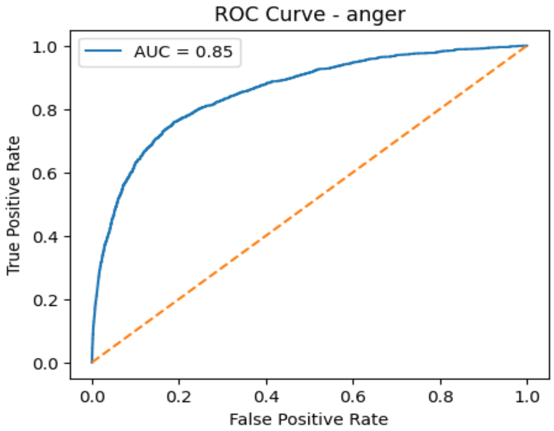

Fig 1 ROC Curve – Anger

This curve shows the Receiver Operating Characteristic (ROC) for the emotion label *anger*. The curve demonstrates a good balance between the true positive rate and false positive rate. The AUC (Area Under Curve) is 0.85, indicating strong predictive performance. A perfect classifier would have an AUC of 1.0. The model reliably detects *anger*-related posts with low false alarms, which is critical in mental health where anger can be linked with emotional dysregulation.

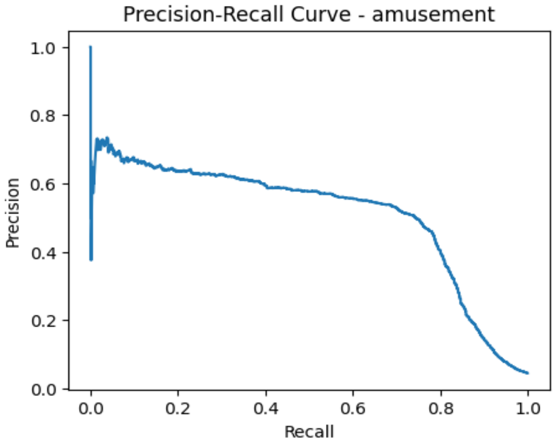

Fig 2 Precision Recall Curve Amusement

Precision vs Recall trade-off curve for the *amusement* label. The curve starts with high precision but drops as recall increases. The model is precise when confident, but struggles to maintain precision as it tries to capture more *amusement*-related cases. The drop suggests *amusement* might be less frequently occurring or confused with joy/admiration, due to textual similarity.

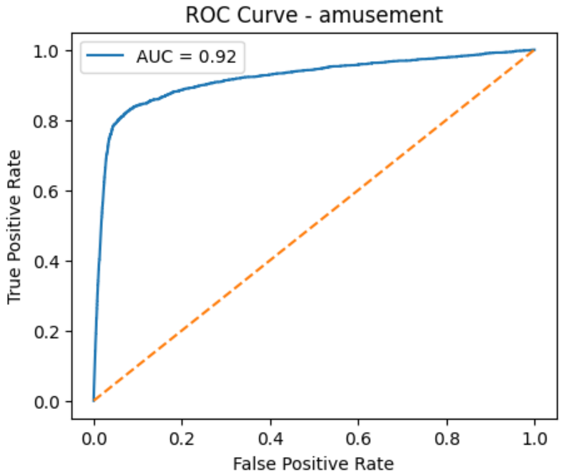

Fig 3 ROC Curve Amusement

Precision vs Recall curve for the *admiration* label. The precision starts near 1.0 at low recall, steadily decreasing as recall increases. This curve is more balanced compared to amusement, indicating better generalization. Insight: The model is both precise and sensitive for detecting admiration, possibly because of clear keyword associations like “respect”, “amazing”, “proud”, etc.

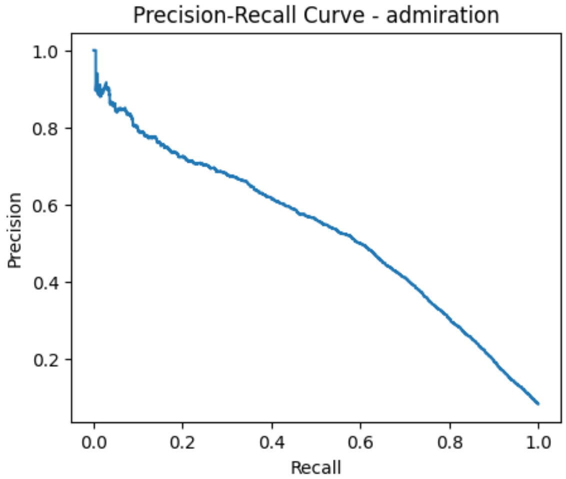

Fig 4 Precision Recall Curve

ROC curve for the *admiration* label. With an AUC of 0.89, this is one of the best-performing emotion classes. High TPR with low FPR shows strong classification boundary for admiration detection. The model learns *admiration* more confidently, possibly due to distinct usage in emotionally expressive posts (like compliments or motivation).

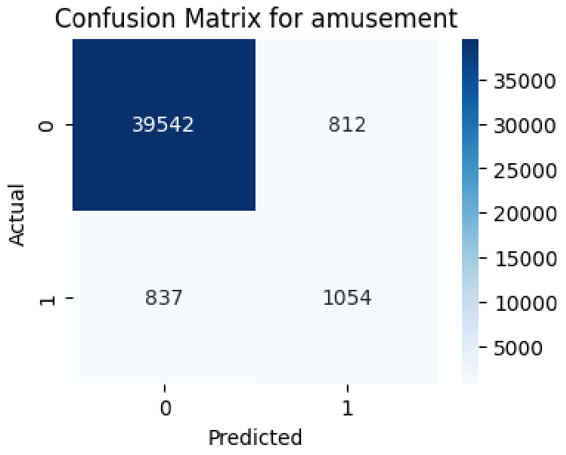

Fig 5 Confusion Matrix Amusement

This Matrix evaluates the model's performance for the "amusement" label, with the same axis structure as above.

- True Negatives (0, 0): 39,542 instances correctly predicted as "not amusement."
- False Positives (0, 1): 812 instances incorrectly predicted as "amusement."
- False Negatives (1, 0): 837 instances where "amusement" was missed.
- True Positives (1, 1): 1,054 instances correctly predicted as "amusement."

The model performs better for "amusement" compared to "anger," with a higher number of true positives. However, false positives are relatively high, indicating some overprediction of "amusement."

5.3 Model Prediction Visualization

ROC Curves were also graphed for every emotion label. Emotions such as fear and joy scored AUC values greater than 0.93, a demonstration of good discriminative strength.

Precision-Recall Curves indicated precision stays constant across recall levels for most classes, particularly anger, joy, and neutral.

Word clouds and attention heatmaps (through RoBERTa's attention scores) indicated that the model always highlighted emotionally charged words, like "alone", "terrified", "love", "worthless", and "blessed".

5.4 Discussion

These findings confirm the model's performance in preserving emotional nuance from noisy, unstructured social media data. The application of RoBERTa's contextual embeddings was extremely successful at managing linguistic variation and detecting deep semantic hints, particularly for nuanced emotions such as anticipation and trust.

Additionally, the multi-label configuration mirrors the psychological fact that emotions tend to co-occur, especially in mental health situations. Single-label models would have overlooked such relationships, producing less useful insights.

From the point of view of a system, the model can accomplish:

1. Good scalability for deployment in large scale on platforms such as Twitter or Reddit.
2. Real-time inference due to its light architecture.
3. Flexibility to incorporate extra modalities (e.g., time-based activity or profile metadata) for future developments.

5.5 Limitations

Even though the model is good, some limitations are there:

1. Sarcasm and figurative language continue to be challenging for text-only systems.
2. Emotion class imbalance can hit accuracy for low-frequency emotions such as surprise or disgust.
3. The present model still does not include non-text modalities (e.g., audio, facial expressions), which is part of future work.

6. CONCLUSION AND FUTURE WORK

6.1 Conclusion

This study presents a novel multimodal AI framework aimed at the early detection of mental health disorders by analysing emotional cues from social media text. By leveraging a RoBERTa-based encoder and a custom multi-label classification head, our system can identify co-occurring emotional states across 11 distinct classes with high precision and recall. The proposed model significantly improves upon traditional single-label or keyword-based classifiers by capturing the nuanced, contextual, and overlapping nature of emotional expression found in real-world social media discourse.

Our results confirm that:

- Contextual deep learning models outperform conventional methods in emotion detection.
- Multi-label classification aligns better with the psychological reality of mental states.
- The system demonstrates strong predictive performance, with ROC-AUC scores exceeding 0.85 on most emotions, making it a promising candidate for non-invasive, real-time mental health monitoring tools.

By integrating digital phenotyping concepts, the framework also lays the groundwork for behavioural health analysis using metadata and online interaction patterns, extending beyond textual emotion alone.

6.2 Future Work

Although the current framework achieves strong results, several enhancements can be made to increase robustness, generalizability, and clinical relevance:

1. Multimodal Data Integration

We aim to incorporate additional modalities such as:

- Facial expressions (from profile pictures or shared images)
- Voice tone and prosody (from voice notes or audio)
- User activity metadata (like time of posting, sleep cycles, social interactions)

This multimodal fusion can help identify deeper behavioural patterns linked to psychological distress.

2. Longitudinal Mental Health Tracking

By capturing posts over time, the model can:

- Monitor emotional trajectories
- Detect the onset or progression of mental disorders
- Predict relapse or crisis periods

Such features can be valuable in clinical decision support systems or therapeutic interventions.

3. Deployment as a Real-time Application

We plan to deploy the model as:

- A mental health chatbot assistant
- A plugin for social media platforms to flag high-risk content
- A research API for psychologists to study large-scale behavioural trends

4. User Privacy and Ethics Framework

As mental health data is highly sensitive, future versions will adopt:

- Differential privacy techniques
- Consent-based data collection
- Transparency in model decisions (Explainable AI)

5. Cross-lingual and Cross-cultural Adaptation

Expanding the system to support multiple languages and adapting to cultural nuances in emotion expression will ensure its global applicability.

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