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SARCASM AND MENTAL HEALTH DETECTION FROM SOCIAL MEDIA USING TRANSFORMER-BASED TECHNIQUES

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ABSTRACT

Social media platforms generate massive amounts of textual content every day, containing valuable information related to human emotions, opinions, sarcasm, and psychological behavior. Understanding such contextual and emotionally implicit information has become an important research problem in Natural Language Processing and Artificial Intelligence. This thesis presents transformer-based approaches for sarcasm detection and mental health classification from social media text using contextual representation learning and Explainable Artificial Intelligence techniques. For sarcasm detection, a transformer-based framework named SarcasmBERTa is proposed by integrating RoBERTa with Multi-Head Attention mechanisms to capture contextual and semantic relationships from multilingual social media text. The framework was evaluated on English, Hindi, and Bengali datasets and demonstrated superior performance compared to several baseline and contemporary models. For mental health detection, the proposed X-MHD framework combines DistilBERT, knowledge graph embeddings, and Explainable Artificial Intelligence techniques. The model effectively identifies emotional well-being conditions such as depression, anxiety, bipolar disorder, and suicide-related behaviour from online textual content.

Chapter 1¹²

INTRODUCTION

The rapid growth of social media platforms such as Twitter, Reddit, Facebook, and Instagram has transformed the way individuals communicate, express opinions, and share emotions in daily life. Millions of users continuously²² post thoughts, reactions, experiences, and personal feelings on online platforms, generating massive amounts of textual data every day. This user-generated content contains valuable information related²⁸ to human emotions, behaviour, sentiment, and psychological conditions. In recent years, researchers have increasingly²⁴ focused on using NLP and AI techniques to analyze social media text for applications such as sentiment analysis, sarcasm detection, emotion recognition, and mental health assessment. The informal and context-dependent nature of social media conversations makes understanding textual meaning a challenging task, particularly when users express emotions through sarcasm, humour, irony, or indirect language. Therefore, developing intelligent and interpretable transformer-based systems for understanding social media text has become an important research area in modern NLP and healthcare-oriented AI applications.

1.1 Problem Statement and Objectives

Social media users frequently express emotions, stress, opinions, and psychological conditions through indirect language, sarcasm, humour, and implicit contextual expressions. Detecting such patterns accurately remains a challenging task due to contextual ambiguity, multilingual variations, and lack of semantic understanding in traditional NLP systems. Existing methods also suffer from poor interpretability and limited capability in understanding low-resource languages.

This thesis addresses these limitations by proposing transformer-based frameworks for sarcasm and mental health detection from social media text using contextual representation learning, attention mechanisms, and Explainable Artificial Intelligence techniques.

1.1.1 Sarcasm Detection Using Transformer-Based Techniques

Sarcasm detection is one of the most challenging problems in Natural Language Processing because sarcastic statements often express meanings opposite to their literal interpretation. Traditional sentiment analysis systems fail to correctly identify such hidden emotional intentions, leading to inaccurate sentiment prediction and contextual understanding.

The objective of this work is to develop a multilingual transformer-based sarcasm detection framework using pretrained language models such as RoBERTa integrated with Multi-Head Attention mechanisms. The proposed approach focuses on improving contextual understanding, semantic feature representation, and sarcasm classification performance across English, Hindi, and Bengali datasets.

1.1.2 Mental Health Detection Using Explainable Transformer Framework

¹ Mental health disorders such as depression, anxiety, bipolar disorder, and suicidal ideation are increasingly reflected in social media conversations. Early identification of such psychological conditions through automated NLP systems can assist researchers and healthcare professionals in understanding emotional well-being and behavioural patterns. The objective of this research is to develop an explainable transformer-based mental health detection framework using DistilBERT, semantic knowledge integration, and Explainable Artificial Intelligence techniques such as LIME and attention visualization. The proposed framework aims to improve classification accuracy, interpretability, and robustness for detecting mental health conditions from social media text.

1.2 Motivation

Increase in expansion of social media platforms has significantly increased the amount of user-generated textual data containing emotions, opinions, sarcasm, humour, and psychological expressions. Platforms such as Twitter, Reddit, and Facebook have become important spaces where individuals openly express their thoughts, frustrations, emotional stress, and mental

health conditions. This growing availability of textual data has motivated researchers to explore advanced Natural Language Processing (NLP) techniques for understanding human behaviour and emotional patterns from online communication. One of the major motivations behind this research is the limitation of traditional sentiment analysis and machine learning approaches in understanding contextual and implicit meanings present in social media text. Sarcasm often conveys emotions opposite to the literal meaning of a sentence, making sentiment understanding highly challenging. Incorrect interpretation of sarcastic statements can negatively affect emotion analysis and downstream applications such as mental health prediction systems. Many individuals express their psychological conditions indirectly through sarcastic or emotionally complex statements on social media platforms. Therefore, accurate detection of sarcasm and contextual understanding becomes essential for improving mental health analysis systems. BERT, RoBERTa models provide the capability to capture long-range contextual dependencies, implicit meanings, and emotional cues more effectively than traditional deep learning approaches. This motivated the use of transformer-based frameworks for both sarcasm detection and mental health classification tasks. Furthermore, most existing systems operate as black-box models and lack interpretability, which reduces trustworthiness in healthcare-related applications. To provide transparent and interpretable predictions, XAI techniques such as LIME is used.

The motivation of this thesis is therefore to develop an efficient, multilingual, and explainable transformer-based framework capable of accurately detecting sarcasm and mental health conditions from social media text while improving contextual understanding, robustness, and prediction interpretability.

Chapter 2

LITERATURE REVIEW

The rapid advancement of NLP and AI has improved the analysis of social media text for applications such as sentiment analysis, sarcasm detection, emotion recognition, and mental health assessment. Social media platforms generate large volumes of user-generated textual data containing opinions, emotions, humour, and psychological expressions. Researchers have increasingly explored machine learning, deep learning, and transformer-based approaches to understand contextual meaning and emotional behaviour from such data.

2.1 Baseline and Deep Learning-Based Models

Ahuja and Sharma [2] propose the LMTweets encoder model for sarcasm and irony detection, trained on 500,000 tweets. Cambria et al. [35] proposed a multi-task learning framework based on a deep neural network to model the connection between sentiment and sarcasm while simultaneously solving both tasks. Cai et al. [9] developed a multi-modal sarcasm detection model for Twitter that combined text, images, and image attributes. Their hierarchical fusion model first extracted features from each modality and then integrated them using a bidirectional LSTM network. Zhang et al. [57] created ConAttSD, a model designed to detect sarcasm in multimodal situations, like video conversations. Use of a contrastive attention mechanism, which highlights the differences between positive text paired with a negative tone. Collection of 1.3 million sarcastic statements from Reddit that were self-annotated, which was the largest sarcasm dataset done by Khodak et al. [27]. Rosid et al. [31, 46] developed a hybrid model called MHA-CovBi for detecting sarcasm in Indonesian-English mixed-code texts. The model combined CNN with multi-head attention and BiGRU, using Fast-Text for Indonesian and GloVe for English word embeddings. Pandey and Singh [40] proposed a sarcasm detection model by combining LSTM and BERT for code-mixed language. Yue et al. [56] developed KnowleNet, a

multimodal sarcasm detection model that used ConceptNet to incorporate prior knowledge and improve understanding of image-text by detecting cross-modal semantic similarities. A new hybrid model was created by Hazarika et al. [19] that tried to detect sarcasm by analyzing authors' past behavior in comments and studying the general behavior of authors within specific subreddits. Bao et al. [5] introduced the HIAN model to address the challenge of aligning diverse sarcasm cues from text and images. It utilized a BiLSTM with interactive attention to extracting richer textual features by integrating visual class words. Application of machine learning (ML) techniques for analyzing mental health has been widely investigated in previous studies. Early research work mainly focused on traditional techniques of ML models to detect emotional and psychological patterns in textual data. Kaushik et al. [25] studied classical algorithms, including SVM, also Logistic Regression, and Multinomial Naïve Bayes, for sentiment analysis on mental health datasets. Focusing on early detection and intervention, D'Cruz et al. [16] developed ML classifiers based on some contexts gathered from Twitter and Reddit to predict depressive tendencies based on user-generated posts. Similarly, Chen et al. [13] introduced the psychological effects of the COVID-19 pandemic through textual analysis of comments on the website Reddit that were sourced from mental-health related datasets, such as anxiety, depression, SuicideWatch, extending this line of research to multilingual environments, Dwivedi and Rao [15] introduced a hybrid architecture that combines Recurrent Neural Networks (RNNs) with Bidirectional LSTM (Bi-LSTM) models for identifying mental health-related signals in multiple languages. Sharma et al. [49] proposed the ML methods for analyzing mental fitness issues in workplace environments. A significant breakthrough in natural language processing began with the advent of the architecture based on transformer proposed by Vaswani et al. [52]. This paradigm shift marked the beginning of influential pretrained text models, become central to mental health and sentiment analysis since.

2.2 Transformer and Pretrained Language Model (PLM)-Based Models

A new approach for sarcasm detection that used context from parent comments on Reddit is proposed by Yang et al. [55]. They worked with the

SARC dataset and employed a pre-trained XLNet model to extract features. An approach for detecting sarcasm in Twitter posts using the transformer model has been proposed by Gregory et al. in [18]. The authors also used LSTM, GRU [38] and transformer models. The top-performing model in this approach is an ensemble of transformer models, including BERT, RoBERTa [32], XLNet [55], RoBERTa-large, and ALBERT [30]. At some points in the text, an emoji is used, followed by how it is interpreted by the model, and then how it is used in a model which incorporates it SEEmoji MUSTARD [12], an extended dataset which includes emojis and uses them for sentiment and emotion annotations for better sarcasm detection in multimodal conversations. MUSTARD dataset [11] is utilized for multimodal-based sarcasm detection. The dataset is based on TV shows, which consist of audio-visual dialogues with sarcasm labels and the dialogue history. Internet community sites such as Reddit and Twitter are highly populated with figurative language. Nikhil Jaiswal [24] suggested a deep neural structure for the detection of sarcasm. He utilized pre-trained language models such as BERT and RoBERTa. He then used them to improve their performance on a Twitter dataset. A sarcasm detection model is proposed by Meng et al. [37], combining BERT and an attention mechanism to address the challenge of detecting sarcasm in sentences with complex semantics and few sentiment words. However, sarcasm’s implicit nature makes it challenging to detect, [3], particularly in Bangla, where research remains limited compared to English. Anan et al. introduced a BERT-based model, which was much better than traditional data-driven techniques. To test their approach, they created BanglaSarc, a new Bangla sarcasm dataset made up of comments from Facebook and YouTube. HumourHindiNet, a framework for detecting humor in Hindi web series, was created by Kumar et al. [28]. They built a new multimodal dataset using dialogues from shows like ‘Kota-Factory’ and ‘Panchayat’, which were manually labeled as humor or non-humor. Pramanick et al. [42] introduced a new framework called MuLOT (Multimodal Learning using Optimal Transport). This framework has been tested using benchmark datasets such as MUSTARD, UR-FUNNY, and MST. [10]. Combining textual linguistic features with visual information, the multimodal sarcasm detection approach was proposed by Han et al. [9]. Their model focused on the textual modality, extracting high-frequency characters from pure text and hashtag [21] to create a third modality alongside images and text. Qin et al. [43] created MMSD 2.0, an improved version of the original MMSD dataset, to fix problems like misleading cues and unrealistic negative sample. Some-

times language comes into the problem. Bedi et al. [6] developed MaSaC, a Hindi-English code-mixed dataset for sarcasm detection and humor classification in conversations, and proposed MSH-COMICS, an attention-rich neural model. Liang et al. [31] introduced an approach to address the challenge of identifying sarcasm using both text and images. The method employed object detection and OCR to extract key visual and textual cues, which were modeled using multimodal graphs. A graph-based contrastive learning strategy was proposed to enhance modality interaction and representation. In multimodal, we need to combine text, images, and image attributes. A huge corpus of Bengali text for the specific problem of research on sarcasm detection in Bengali, named ‘Ben-Sarc,’ comprising a total of 25,636 comments gathered manually from various Facebook public pages and rated by external evaluators, was proposed by Lora et al. [33]. Pokhriyal and Jain [41] proposed a sarcasm detection approach for Hindi social media comments using a probabilistic non-linear optimization technique integrated with word embeddings. For the Algerian dialect, Bousmaha et al. [8] introduced an integrated multimodal approach to sarcasm detection by utilizing both visual cues through VGG-19 and text cues through EasyOCR with some linguistic properties and machine learning algorithms. Zhang et al. [58] proposed a Multimodal Interaction Learning (MIL) framework for joint sarcasm and sentiment detection that employs cross-modal target attention and a dual-gating network to capture shared and task-specific features across modalities. Rodríguez et al. [45] proposed SINCERE, a hybrid graph-based sarcasm detection framework that integrates sentiment and emotion analysis using distant supervision and graph-based latent representation learning. Zhang et al. [59] introduced AMSD Dataset and the SarcasmBench benchmark to evaluate sarcasm understanding across 16 LLMs. While previous models performed well on certain datasets, they still had limitations in multilingual and low-resource settings. By addressing this issue we proposed a model that overcame these limitations and achieved good performance. Refai et al. [44] proposed a multi-dimensional prompt evaluation framework for LLMs that assesses prompts based on similarity, performance, efficiency, and consistency across several Arabic NLP tasks—including sarcasm detection—using models such as GPT-4o mini, LLaMA, and Claude 3.5 Haiku, highlighting trade-offs between prompt effectiveness and computational efficiency. Bade et al. [4] investigated pragmatic generalization of LLMs for multilingual sarcasm detection by fine-tuning encoder models such as BERT, RoBERTa, XLM-RoBERTa, and DistilBERT, while comparing them with few-shot GPT-4o,

showing that fine-tuned models significantly outperform generative LLMs in cross-lingual sarcasm detection tasks. According to Ou & Li et al. [39], a multi-granularity information fusion network can be used for the detection of multimodal sarcasm using multi-task CLIP and global-local cross-modal interaction learning. Various machine learning and deep learning architectures, including Random Forest, XGBClassifier, fastText-stackedTCN, and mBERT, were explored by Ahmad et al. [4] on a dataset of 1,945 humorous Hindi newspaper headlines from Hindustan and Dainik Jagran. Although previous models achieved success on certain datasets, they are still not sufficient for low-resource and multilingual scenarios. We proposed a model that transcends these limitations and achieves success on these problems. Bikku et al. [7] assessed the performance of BERT on large-scale sentiment analysis on social media data. In a comparative study, Joshy et al. [24] assessed in mental health domain using BERT, DistilBERT, RoBERTa. Ji et al. [22] introduced two model MentalBERT and MentalRoBERTa, which were pretrained on Reddit data from mental health communities. In a related effort, Vajre et al. [51] proposed PsychBERT, a model pretrained on a combination of biomedical literature and mental health-focused social media data. Madhuri et al. [23, 32] introduced a mental health screening approach for homeless children by analyzing responses to the Pediatric Symptom Checklist (PSC) by using a SVM model. Kumar et al. [29] proposed a smartwatch-based deep learning framework for mental stress detection that addresses the limitation of missing respiration rate in wearable sensors. Sarode et al. proposed [48] a decision support model to assess Mental Health Literacy (MHL) by segmenting individuals in academic communities using modifiable predictors. Addressing the difficulties related to data scarcity also the lack of open-source mental health-focused LLMs, MentalLaMA, an open-source LLM family built upon the LLaMA2 architecture is proposed by Yang et al. [54]. Yadav et al. [47] introduced an AI-powered mental wellness chatbot that leveraged generative AI and embedding-based relevance detection to deliver context-aware and empathetic responses. Marrapu et al. [36] proposed a data science-based model for predicting public mental health conditions using sensor data and healthcare datasets. Existing studies rarely combine contextual language modeling, structured knowledge integration, and explainable AI within a unified framework. Taking inspiration from it, our paper introduces a novel hybrid architecture, named X-MHD, which incorporates DistilBERT representations, knowledge graph embeddings, and explainable artificial intelligence to achieve interpretable mental health clas-

sification which consists multiple classes using text taken from social media. The next section overviews the architecture and components of the proposed X-MHD approach.

Chapter 3

METHODOLOGY

3.1 Overview of Proposed Framework

The proposed framework integrates contextual language understanding, semantic feature representation, attention mechanisms, and interpretability to improve classification performance and prediction transparency. The proposed framework consists of two major components: multilingual sarcasm detection and explainable mental health detection. For sarcasm detection, a pretrained RoBERTa model integrated with Multi-Head Attention (MHA) mechanisms is utilized to capture implicit semantic relationships and contextual cues present in sarcastic expressions. For mental health detection, DistilBERT along with knowledge graph embeddings is employed to enhance semantic understanding of psychological concepts and emotional patterns. Sarcasm detection and mental health analysis are closely connected research problems because users often express emotional distress, stress, anxiety, or frustration through sarcastic and indirect language. Incorrect interpretation of sarcastic statements may negatively affect mental health prediction systems. Therefore, contextual understanding of sarcasm plays an important role in improving emotional and psychological analysis from social media conversations.

3.1.1 Sarcasm Detection Framework

Data Processing

We start with data that is already public, although it is not clean. It is raw and contains clutter like URLs and image IDs. The data used in this work is from KnowleNet, which needs to be cleaned. For ‘Ben-Sarc,’ the labels are already provided as “sarcasm” and “not sarcasm.” For our work, we standardize the labels by using 1 for “sarcasm” and 0 for “not sarcasm.” We use the same labels for all the data. While cleaning the data, we realized that there are duplicate data in some of the data sets, such as ‘Ben-Sarc’ and Hindi. For ease, we also clean the paragraph formatting in the Hindi data. For k-fold validation, we use all the validation, test, and training data in one

dataset for each language, such as English, Hindi, and Bengali. Our method helps in making the process of preprocessing and validation in various data sets efficient.

Tokenization: Preprocessing Text for Model Input

Roberta tokenizer is used in this paper. This tokenizer is important in facilitating the transformation of the unstructured input into an understandable language for the model. This tokenizer is initialized with the weight parameters of the 'roberta-base' model from Hugging Face. To ensure standardization in input data, truncation, and padding were used where necessary.

- Truncation: Inputs with more than 256 tokens were truncated to the defined max limit, emphasizing key content.
- Padding: Tokens were used for shorter input texts to ensure consistency in data format.

For each input text, tokenization produces two outputs: attention masks and token ID outputs. The model is capable of processing text data in numerical form, token ID, which is an integer value allocated to each token. The attention masks represent valid token positions (1) and padding positions (0). The tokenizer processes inputs in batches, thereby minimizing time delay in data flow.

Model Design and Training Approach

The enhanced model structure for the sarcasm identification challenge is based on the RoBERTa model. The multi-head attention method (Fig. 1) is used to enhance the understanding of the context in the text parts. Avoiding overfit is important things so layer Norm and dropout rate 0.3 are used. Which helps in stability during the training process. The output of the RoBERTa model is classified using a classifier. The weighted loss function [0.7, 1.3] is used to enhance the model to take care of class balance in the dataset. The optimization process is carried out using the AdamW optimizer with a learning rate of 1e-5. For the fine-tuning of the training process, the cosine annealing schedule with warm restarts is used. This schedule gradually decelerates the learning process and restarts it at regular intervals. This helps the model avoid the local optima and converge better. The above-discussed strategies are the most optimized and balanced approach for the

problem of sarcasm detection. The proposed SarcasmBERTa model process is illustrated in Figure. 2. Raw data collection marks the first step in the process. Raw data will then be subjected to the data preprocessing step where it undergoes several procedures such as data cleaning through the process of lemmatization, stemming, replacement of emojis with texts, among others. After going through the data preprocessing stage, the data will then be tokenized using the RoBERTa Fig. 1 model's tokenizer. This model employs the K-Fold Cross-Validation technique for training, and the tokenized input data will be replicated five times.

Tokenizing the Input Text

Let's take an input text T , to process it, we first tokenize it using a pre-trained tokenizer which is the RoBERTa tokenizer. The tokenizer converts the text into a sequence of integer token IDs, ensuring a fixed-length L using padding or truncation. This fixed-length token sequence becomes the input to the model. Here, X is a function of T , representing a sequence of token IDs produced by the tokenizer.

$$X = \text{Tokenizer}(T) = \{x_1, x_2, \dots, x_L\}, \quad x_i \in \mathbb{Z} \quad (3.1)$$

where x_i represents the token ID for the i -th token in the sequence.

Generating Contextual Embeddings with RoBERTa

As we get the tokenized input, X it is passed through the pre-trained RoBERTa model. It produces contextual embeddings for each token, incorporating the context of the surrounding tokens. These embeddings form a matrix H representing the entire input sequence.

$$H = \text{RoBERTa}(X, M) = \{h_1, h_2, \dots, h_L\}, \quad h_i \in \mathbb{R}^d \quad (3.2)$$

Here $H \in \mathbb{R}^{L \times d}$ is the hidden state matrix. $M \in \{0, 1\}^L$ is the attention mask indicating valid (non-padded) tokens. The RoBERTa hidden layer has a dimensionality of d .

Refining Representations via Multihead Self-Attention

While the conventional attention mechanism in the RoBERTa transformer architecture is already employed, an additional MHA layer is added on top of

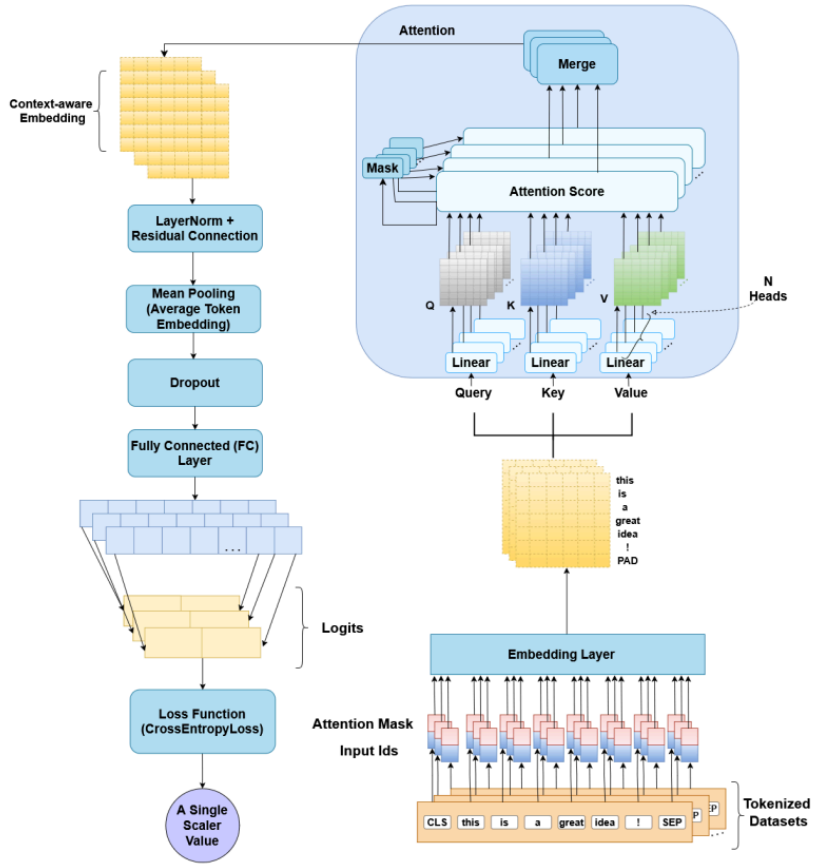


Figure 3.1: Architecture of the proposed sarcasm detection SarcasmBERTa model

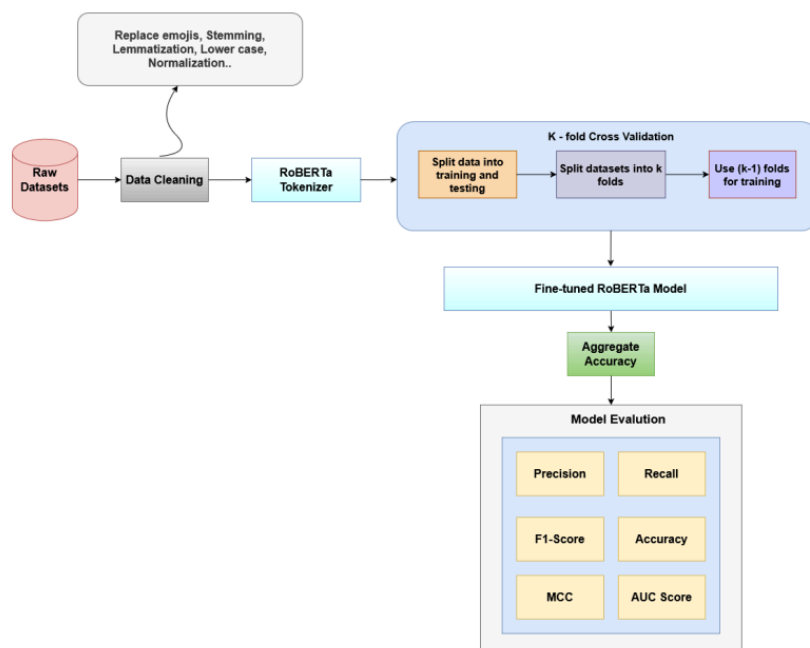


Figure 3.2: Workflow of the Sarcasm Detection Model, i.e., SarcasmBERTa

the context-aware representations to enhance token-level interactions specific to sarcasm contexts. Multihead attention is a good approach for contextual understanding in text. So, to further enhance the contextual representations, a multihead self-attention mechanism is applied.

All attention head outputs are concatenated, which allows the model to project the resulting vector back into the original embedding space.

$$H' = \text{Concat}(\text{Attention}_1, \dots, \text{Attention}_k)W_O \quad (3.3)$$

where $W_O \in \mathbb{R}^{d \times d}$ is the output projection matrix.

To enhance the stability and efficiency of training, we add a residual connection into the model architecture.

$$H'' = \text{LayerNorm}(H' + H) \quad (3.4)$$

Mean Pooled Sequence Representation

Mean pooling is done on the token embeddings in order to obtain a fixed-size representation of the sequence. The mean pooling works by averaging the values of the token embeddings, ensuring the resulting vector captures the sequence's overall characteristics. Moreover, it minimizes the effect of single tokens, making it possible for the model to pay attention to the whole sequence. This technique proves efficient in obtaining a brief and fixed-size representation of the sequence.

$$P = \frac{1}{L} \sum_{i=1}^L h_i'' \quad (3.5)$$

The resulting vector $P \in \mathbb{R}^d$ serves as the global representation of the input sequence.

Classification Layer for Sarcasm Detection

To avoid overfitting, a dropout layer is used on the pooling vector P . Another dense layer, which is completely connected, processes the vector after dropout. This layer transforms the pooled vector into logits, which are class-specific scores. It enables the model to make predictions on all classes. To increase the robustness of prediction, we use dropout before classifying, and

a fully connected layer provides raw prediction values for both sarcasm and non-sarcasm labels.

$$Z = W_F P + b, \quad Z \in \mathbb{R}^C \quad (3.6)$$

where $W_F \in \mathbb{R}^{d \times C}$ is the weight matrix, $b \in \mathbb{R}^C$ is the bias vector, $C = 2$ is the number of output classes (Sarcastic, Non-Sarcastic). The softmax function is used to forecast the probabilities of the classes:

$$\hat{y} = \text{softmax}(Z) \quad (3.7)$$

Training with Weighted Cross-Entropy Loss

During training, a weighted cross-entropy loss function is used to handle the imbalance of the dataset:

$$\mathcal{L} = -\frac{1}{N} \sum_{i=1}^N w[y_i] \log(\hat{y}_{i,y_i}) \quad (3.8)$$

where y_i is the true label of the i -th sample, $\hat{y}_{i,y_i}$ is the predicted probability of the true class, $w[y_i]$ is the class weight for y_i , N is the batch size.

Optimizing with AdamW and Learning Rate Scheduling

Model parameters are optimized using AdamW optimizer, which is a variant of Adam that decouples weight decay from the d=gradient update. In addition to the optimizer, we employ a learning rate scheduler to control the pace of learning over time. Initially, a warmup phase is applied to gradually increase the learning rate, which helps stabilize early training and prevent large, unstable updates. This combination of AdamW and learning rate scheduling improves both training efficiency and final accuracy.

$$\eta_t = \eta_0 \cdot \text{cosine_annealing}(t) \quad (3.9)$$

where η_0 is the initial learning rate and t is the current training step.

Evaluating with K-Fold Cross-Validation

The K-Fold Cross-Validation technique is utilized to ensure reliability and universality because the model is trained using $K - 1$ folds and tested using

the last fold. In addition, among those included in the evaluation metrics are Loss, F1-Score, and Accuracy. The mean of the parameters obtained from each fold represents the final result.

Dataset and Evaluation Metrics

There are a total of five datasets. These datasets are for English, Low Resource Language, Hindi, and Bengali. The descriptions of the datasets are as follows:

English

33,859 English tweets are annotated as 1 for sarcasm and 0 for non-sarcasm. The data is cleaned up by removing columns, hence only retaining the required columns. There are 17,598 non-sarcastic tweets, and 16,261 tweets are sarcastic [10].

Bengali.

Lora et al. [33] create a dataset 'Ben-Sarc' (A Dataset for Sarcasm Detection), 25,636 balanced datasets combination of equal division of sarcastic and non-sarcastic datasets.

Hindi

Katyayan introduced [24] a collection of a total of 16,000 Hindi tweets, where 6,051 tweets are sarcastic and 10,128 tweets are non-sarcastic. Kumar et al. include [28] "Panchayat" – a Hindi web series from HumourHindiNet, which offers 3,000+ humor-rich dialogues. "Kota Factory" – another Hindi web series from HumourHindiNet – consists of 2,000+ sarcastic dialogues.

Evaluation Metrics

In the current section, we provide justification for various metrics used for their performance measures based on our recommended algorithm. The explanations for these metrics are mentioned below:

1. **Accuracy (Acc):** Accuracy reflects the ratio of correctly predicted instances out of the total. In simple terms, it tells you how often the

predictions are right. Mathematically, it is:

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \quad (3.10)$$

2. **Precision (Pre):** Precision tells us how many of the things we call positive are actually correct. In simple terms, it shows the accuracy of our positive predictions. Mathematically, we write it as:

$$Precision = \frac{TP}{TP + FP} \quad (3.11)$$

3. **Recall (R):** Recall is a performance metric that calculates the ratio of genuinely positive instances labeled correctly. Recall can be formulated mathematically for a binary classification problem as:

$$Recall = \frac{TP}{TP + FN} \quad (3.12)$$

4. **F1 Score (F1):** Harmonic mean (F1 Score) refers to the compromise between recall and precision. This means that the performance of the model is determined by taking both accuracy and ability to capture all positive examples into consideration. The formula used to determine it is:

$$F1 \text{ Score} = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \quad (3.13)$$

5. **Consistency Loss (CL):** Consistency Loss calculates the reliability of predictions made by the model in case of minor changes in the input text. For sarcasm detection models, minor changes in word choice and representations should not affect the output class predictions, provided that the semantics remain unchanged. Thus, consistency loss is the measure of dissimilarity between the probability distributions predicted by the model on the input and its perturbation. Let x be the input text, and let $\tilde{x}$ denote a perturbation of the same text obtained using the method of random dropout through forward propagation. The probability distributions corresponding to the respective inputs are denoted as $p(x)$ and $p(\tilde{x})$. This loss is shown below:

$$CL = ||p(x) - p(\tilde{x})||^2 \quad (3.14)$$

When the consistency loss takes a smaller number, this means that the model provides consistent predictions against small disturbances, which suggests that it is more robust.

6. **MCC:** It ranges from -1 for inverse prediction to $+1$ for perfect prediction in the case of binary classification. A perfect prediction is shown by $+1$, an average random guess is shown by 0 , and an inverse prediction is shown by -1 . Matthews Correlation Coefficient (MCC) is particularly useful in cases of unbalanced classes because it considers the imbalance in the calculation. Its mathematical expression is:

$$\text{MCC} = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (3.15)$$

7. **ROC Curve (Receiver Operating Characteristic Curve):** is a graphical representation of the performance of a binary classification model for all classification thresholds. Using the ROC curve, we can now also compare different classification methods. Mathematically it is written as:

$$\text{TPR} = \frac{TP}{TP + FN}, \quad \text{FPR} = \frac{FP}{FP + TN} \quad (3.16)$$

3.1.2 Mental Health Detection Framework

Data Collection

Experiments have been performed using the Reddit dataset, called the Reddit Suicide Watch and Mental Health (SWMH), which consists of a number of mental health-focused subreddits from the Reddit platform [21]. The dataset primarily consists of posts related to issues like depression, anxiety, and bipolar disorder. These are all mental health based. The dataset contains a total of 54,412 labeled posts, which makes it a complete dataset for mental health classification tasks. The dataset has five tags: Anxiety, bipolar, depression, SuicideWatch, and offmychest. Also all tags having prefix "Self.". It is divided into a data to train, data for validation, and data to test in a ratio of 70:10:20. The labels have been remapped to Anxiety, Bipolar, Depression, Suicide, and None, respectively, for better interpretation of the results. The OffMyChest category has been included as a neutral category, which does

not indicate any mental health disorder. The posts included in this category express emotional content but do not indicate any particular mental health disorder.

Data Processing

The social media texts on mental health issues might contain informal writing, irrelevant information, and contradictions. To guarantee high-quality input, the following preprocessing steps are taken:

- Noise removal: removal of URLs, HTML tags, mentions, hashtags, and other non-text symbols
- Normalization: converting all input characters to lowercase and limiting excessive character repetition (e.g., replacing “soooo” with standard whitespace normalization)
- Text standardization: unicode normalization and stop word filtering, as appropriate
- Label encoding: applying a multi-class encoding scheme on mental health categories, which includes:
 - Depression
 - Suicide Watch
 - Disorder Off (Note: The category names can be modified according to the exact categorization scheme used)

Knowledge Graph Construction and Integration

To enrich contextual representations with structured semantic knowledge, we incorporate a domain-specific knowledge graph (KG) representing relationships among mental health concepts. The knowledge graph consists of entities such as symptoms, emotional expressions, psychological states, and mental health conditions extracted from mental health lexicons and Reddit mental health discussions.

Each entity in the knowledge graph is represented using the TransE embedding method, which learns low-dimensional vector representations by modeling relationships between entities as translation operations in the embedding space. Formally, the embedding model optimizes the relationship:

$$\mathbf{h} + \mathbf{r} \approx \mathbf{t} \quad (3.17)$$

The head and tail entity embeddings are denoted by $\mathbf{h}$ and $\mathbf{t}$, respectively, and $\mathbf{r}$ represents the relation embedding vector.

The resulting knowledge graph embeddings provide semantic representations of mental health concepts that complement the contextual embeddings produced by DistilBERT. These embeddings are then integrated with textual representations during feature fusion by enhancing the capturing ability of model implicit psychological signals. The contextual representation obtained from DistilBERT and the knowledge graph embedding are fused using feature concatenation:

$$\mathbf{h}_{\text{fused}} = [\mathbf{h}_{\text{text}}; \mathbf{h}_{\text{KG}}] \quad (3.18)$$

where $\mathbf{h}_{\text{text}}$ represents contextual embeddings generated by DistilBERT and $\mathbf{h}_{\text{KG}}$ represents knowledge graph embeddings.

Large Language Models

Emotional well-beings prediction problems are evaluated by a number of text-based (language) models to check effectiveness

- BERT: This ²⁴ model was fine-tuned to apply the model to the SWMH dataset.
- RoBERTa: This ¹² is an optimized version of the BERT model. It was fine-tuned to enable performance comparisons with the baseline model.
- MentalBERT and MentalRoBERTa: These are domain-specific transformer models that were trained on text data related to mental health. They were used directly.
- MentaLLaMA: This is a language model based on the LLaMA2 model. Evaluation was done in predicting mental health outcomes.
- ¹ BART-Large-MNLI: Zero-shot classification was used to predict mental health classes independently.

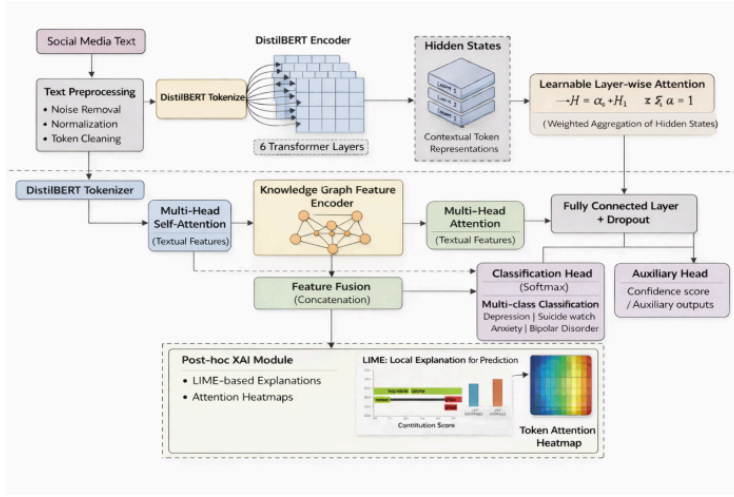


Figure 3.3: Overall architecture of the proposed X-MHD model integrating DistilBERT, Knowledge Graph features, and LIME-based explainable AI for multi-class mental health disorder detection.

Evaluation Metrics

For evaluating the model comprehensively, various metrics were used:

- Accuracy: This metric calculates the overall accuracy of predictions made by the model.
- Classification Report: This metric provides detailed information regarding precision, recall, and F1 score for different classes.
- Confusion Matrix: Calculation of true positives, true negatives, false positives, and false negatives is done. These are needed to create confusion matrix.

Multi-Task Learning Framework

To improve model robustness and generalization, we adopt a multi-task learning framework consisting of a primary classification task and an auxiliary prediction task. The primary task performs multi-class classification of mental health conditions, while the auxiliary task predicts a confidence score indicating whether the input text expresses mental health related distress.

The overall training objective is defined as a weighted combination of the two loss functions:

$$L_{\text{total}} = L_{\text{main}} + \lambda L_{\text{aux}} \quad (3.19)$$

where L_{main} represents the multi-class classification loss and L_{aux} denotes the auxiliary task loss. The parameter λ controls the contribution of the auxiliary task during training.

Hyperparameter Settings

The proposed X-MHD model employs *DistilBERT-base-uncased* as the pre-trained language encoder, consisting of six transformer layers. Maximum sequence length of 256 is used to tokenize input texts. In this model batch size is 32. AdamW optimizer at a learning rate of 1×10^{-5} . To reduce overfitting, a dropout rate of 0.3 was applied to fully connected layers. The multi-head attention module utilizes eight attention heads, while the knowledge graph encoder generates embeddings of dimension 50. A class-weighted cross-entropy loss is adopted to address class imbalance, complemented by an auxiliary loss weighted at 0.3 to improve training stability. The model is trained for 10 epochs with 100 warm-up steps, and performance's evaluation is done using 5-fold cross-validation, with all hyperparameters kept fixed across folds to ensure reproducibility.

Chapter 4

RESULT & ANALYSIS

4.1 Results for Sarcasm Detection

Here, we explained the experimental comparison of the methodology developed. We performed experiments on the data sets given in Section 4, and performance was measured by metrics as mentioned in Section 5. This enabled us to evaluate how well our proposed method identifies negative stances in multilingual social media posts. In addition, we compared our approach with several baseline algorithms, including TextCNN [12], and Bi-LSTM [17], to gain a more comparative study.

Evaluation of the model was performed against a variety of existing modern-day sarcasm detection models, including those proposed by Zhang et al. [53], Tay et al. [50], Devlin et al. [26], Xiong et al. [2], [53], and Nguyen et al. [38]. Table 1 illustrates the hyperparameters used to enhance the performance of the model. The batch size used in this case was set to 346 for efficiency, and the max length was set to 256 to ensure context. The learning rate was set to 1e-5, and the model was trained for 50 epochs. For efficient training, 100 warm-up steps were used. The dropout rate was set to 0.3 to ensure that overfitting was avoided. For the multi-head attention, the number of heads was set to eight. The model used the RoBERTa model to perform the role of a transformer. The model also used multi-head attention to ensure that it effectively extracted all the information from the text. In the context of effective training process stability, the model utilizes the concept of ‘Layer Normalization.’ For the purpose of efficient regularization, the model utilizes regularization. In the context of the optimization process for the fine-tuning phase, the model utilizes the concept of ‘AdamW.’ A ‘cosine annealing’ learning rate scheduler is utilized to efficiently plan the learning rate. In the context of effectively addressing the ‘class imbalance,’ the model utilizes the concept of ‘class weighting.’

4.1.1 Hyperparameter Study

A specific number of parameters is used, which include batch size, epochs, warmup steps, learning rate, etc. In this section, the hyperparameters of the model are examined. Max length represents the input token's maximum sequence length. When this value is increased, Batch size is needed when max length become high. When the batch size is high, it enables the model to learn better without using up a lot of memory. The number of times the model iterates over the entire dataset is determined by epochs, which helps in preventing overfitting using early stopping or validation monitoring. The gradual increase in the learning rate using the number of steps in warmup is used to prevent sudden changes in the model weights. When a lower learning rate is chosen, Fine-tuning of pre-trained models like BERT or RoBERTa, which is beneficial in retaining the knowledge that is already learned in the model. Dropout is a regularization method where some of the input elements are randomly set to zero during training. This is beneficial in preventing overfitting by not letting the model get too dependent on certain neurons or features. Representational ability is improved in the model through the use of attention heads, enabling it to pay attention to various parts of the input at once. Class imbalance is addressed by assigning weights to each class within the loss function in order to improve classification performance. AdamW is an optimizer variant that stands for Adam with Weight Decay. It is beneficial in dealing with L2 regularization or weight decay, especially in transformer-based models like BERT, RoBERTa, etc. The scheduler is used to control the learning rate during training, which is beneficial in helping the model converge faster with high accuracy.

4.1.2 Performance comparison with Baseline Algorithms and Contemporary Models

This section sought to assess how well the proposed algorithm performed in comparison to a number of baseline algorithms, including TextCNN, Bi-LSTM, and GloVe. To achieve this, the baseline algorithms are refined for optimal performance. The performance of the proposed algorithm was compared to a number of existing algorithms as part of the experimental study, such as those by P. Zhang et al. [53], Y. Tay et al. [50], J. Devlin et al. [26], and D. Q. Nguyen et al. [38]. Table 3 shows the Correct Rate, Exactness, Sensitivity results, and Harmonic Mean respectively for these algorithms and

ours over the entire set of datasets 1. Analysis of these results demonstrates that our algorithm ranks highest in terms of performance across all datasets and metrics. In Dataset 1, for the English datasets we used Matthews' correlation coefficient (MCC), for each test fold. The model achieved consistently high MCC scores. The highest MCC score was 0.9211, reflecting the model accurately identified sarcastic and non-sarcastic cases. Consistency Loss is calculated according to how varied the probabilities of the original text and its altered form are when making a prediction. Given the importance of the context in understanding sarcasm, a good sarcasm detection model must have consistent predictions even after minor changes made to the original input data. This means that smaller CL values will show more consistent predictions. Furthermore, to compare the model with multimodal and hybrid approaches presented recently, MMFN [39] and KFGC-Net [60] were evaluated.

Table 4.1: Performance comparison of the proposed SarcasmBERTa model with baseline and contemporary models on Dataset 1 using Accuracy (Acc), Precision (Pre), Recall (R), F1-score (F1), and Consistency Loss (CL).

Dataset	Method	Acc	Pre	R	F1	CL
English	TextCNN (Chen, 2015)	0.80	0.74	0.76	0.75	0.052
	SIARN (Tay et al., 2018)	0.80	0.75	0.75	0.76	0.049
	SMSD (Xiong et al., 2019)	0.81	0.76	0.75	0.76	0.047
	Bi-LSTM (Graves and Schmidhuber, 2005)	0.82	0.77	0.78	0.77	0.046
	GloVe (Pennington et al., 2014)	0.82	0.81	0.82	0.81	0.045
	BERT (Devlin et al., 2019)	0.84	0.79	0.82	0.80	0.041
	BERTweet (Nguyen et al., 2020)	0.88	0.87	0.88	0.88	0.034
	KnowleNet (Yue et al., 2023)	0.89	0.88	0.84	0.86	0.029
	KFGC-Net (Zhuang et al., 2025)	0.72	0.66	0.70	0.68	0.059
	MMFN (Ou and Li, 2025)	0.78	0.78	0.76	0.77	0.049
	SarcasmBERTa	0.97	0.96	0.96	0.96	0.019

4.1.3 Evaluation on Bengali Datasets

To evaluate our model's performance in Bangla datasets, SarcasmBERTa was used. The capability and scalability of Sarcasm detection in a unique language and culture are provided. After performing the experiments on

our model, it provided high accuracy and precision rates. The experiments performed on our model showed its robustness. Most importantly, it was capable of extracting Sarcasm cues from English and Bangla texts effectively, overcoming the hurdles of different language structures and culture. These experiments and results validate our approach and highlight the scalability of our approach for multilingual Sarcasm classification. The model performed greatly, achieving remarkable results despite syntactic and semantic differences from English. These results validate our approach and highlight its scalability for multilingual Sarcasm detection. In this paper, Indic-Transformers Bengali BERT [20] is also referred to as a short form of ‘I-T Bengali BERT’. Table 3 showed the comparison with other models and our proposed model.

⁴ Table 4.2: Performance comparison of the proposed SarcasmBERTa model with baseline and contemporary models on Dataset 2 using Accuracy (Acc), Precision (Pre), Recall (R), F1-score (F1), and Consistency Loss (CL).

Dataset	Method	Acc	Pre	R	F1	CL
Bengali	TextCNN (Chen, 2015)	0.65	0.64	0.65	0.64	0.061
	Bi-LSTM (Graves and Schmidhuber, 2005)	0.66	0.65	0.66	0.65	0.059
	GloVe (Pennington et al., 2014)	0.66	0.66	0.66	0.66	0.058
	BERT (Devlin et al., 2019)	0.68	0.69	0.64	0.66	0.054
	I-T Bengali BERT (Jain et al., 2020)	0.75	0.74	0.77	0.75	0.041
	KFGC-Net (Zhuang et al., 2025)	0.70	0.68	0.69	0.68	0.058
	MMFN (Ou and Li, 2025)	0.73	0.72	0.72	0.72	0.052
	SarcasmBERTa	0.82	0.82	0.82	0.82	0.026

4.1.4 Evaluation on Hindi Datasets

SarcasmBERTa’s ability to detect sarcasm across different languages was examined using the Hindi Tweets Dataset-3 for Sarcasm Detection, which contained over 16,000 tweets. The dataset [24] included 6,051 sarcastic tweets and 10,128 non-sarcastic tweets, making it a rich resource for sarcasm detection in Hindi. We used this dataset to test SarcasmBERTa’s ability to generalize across the linguistic and cultural aspects of Hindi. The efficiency of SarcasmBERTa in recognizing sarcasm in various conditions was evident from its high accuracy and precision rate. The effectiveness of adapting the

model to the unique syntax and semantics of the Hindi language was evidenced through the results, where the effectiveness of using the approach for detecting sarcasm across multiple languages was clearly demonstrated. It was observed that SarcasmBERTa performed excellently on the dataset. This is came to notice that, SarcasmBERTa performed exceptionally well on the data set, and the results were great. The results proved that this approach was sufficiently powerful to detect sarcasm in various complex contexts. In addition, the results proved that the model had the potential to adapt well to the specific syntactic and semantic characteristics of the Hindi language. The results shown in Table 5 proved that the model was generalizable and successful in multilingual sarcasm detection. We used two additional datasets: Dataset 4 to further evaluate the performance of SarcasmBERTa, which was based on the Hindi web series *Panchayat*, and Dataset 5, based on *Kota Factory*. The data sets used were for the purpose of humor detection, with utterances being classified as either ‘Humor’ or ‘Non-Humor.’ The data sets selected were appropriate because they relate to sarcasm and humor, allowing us to assess SarcasmBERTa’s ability to differentiate between them. The robustness of the model in identifying sarcasms was affirmed upon scrutinizing the data sets, which indicated that the model had excellent accuracy and precision¹⁸ in identifying them in both cases. The comparison of the performance of our proposed model, Sarcasm-BERTa, and other models, both old and new, was demonstrated in Table 4. SarcasmBERTa demonstrated its efficiency in handling all datasets, including English, Bengali, and Hindi.

The evaluation parameters to measure the efficacy of our model, as shown in Table 5, were:

Figure 3 shows loss curves, that there is a general trend of decreasing loss throughout the 50 epochs. Within the first 10 epochs, the loss decreased rapidly from around 0.5 to less than 0.2. This shows that the network is learning and adapting very well. At the same time, the validation loss is also decreasing, albeit with some fluctuations. In the second part of the graph, between epochs 11 and 30, the network continues to reduce its loss steadily, now to below 0.1. At the same time, the validation loss is steady between 0.2 and 0.3. This shows that the network is becoming more consistent in its performance. Finally, in the third part of the graph, between epochs 31 and 50, the loss is very low, now below 0.05, and the validation loss is also low at around 0.2. This shows that the network has been able to minimize its errors without the risk of overfitting.

During the first phase, from epochs 1 to 10, the training accuracy rose

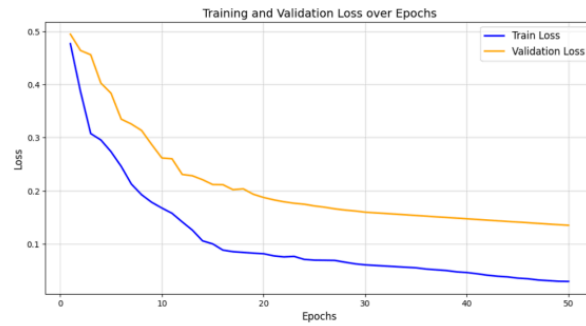
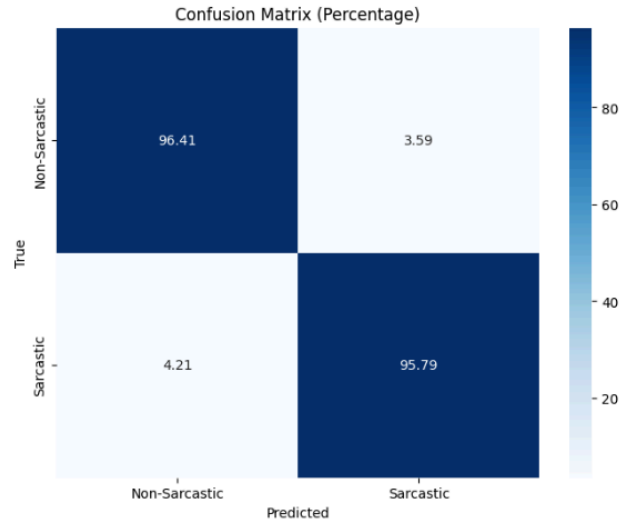


Figure 4.1: Representation of Training and Validation Loss over Epochs



Figure 4.2: Representation of Training and Validation Accuracy over Epochs



27 Figure 4.3: Confusion Matrix for Sarcasm Detection Model

from around 73% to over 90%. At the same time, validation accuracy increased from 78% to about 88%, with only minor fluctuations. In the middle phase, from epochs 11 to 30, the training accuracy exceeded 96%, while the validation accuracy grew steadily, crossing 90%. The gap between the two metrics was very small, indicating that the model generalized well. In the final phase, from epochs 31 to 50, the training accuracy reached nearly 98%, and the validation accuracy reached 96.10% at the end of the 50 epochs. The convergence of both metrics confirmed improvement of our model and the absence of overfitting. The confusion matrix (Fig. 5) showed high level of performance of our proposed model. Both the TP and TN values were well above 90%. Specifically, it was observed that the model correctly classified 95.79% of sarcastic instances and 96.41% of non-sarcastic ones. The FP and FN rates were also very low, at 3.48% and 4.84%, respectively. Misclassifications rates between sarcastic and non-sarcastic texts were minimal, reflecting its competence in recognizing nuanced language patterns.

4.1.5 Ablation Study

An ablation research was carried out with the aim of focusing on the effect of the suggested custom multi-head attention mechanism in order to effectively evaluate the contribution of the suggested components. For this purpose, different improved versions with the incorporation of attention processes were compared with the suggested fine-tuning of the RoBERTa method. The aim behind this research is to evaluate the effect of the suggested custom multi-head attention layer on the model’s ability to effectively recognize contextual sarcastic signals in multilingual datasets. In addition, a consistency regularization term was incorporated during training to encourage stable predictions for perturbed inputs. This regularization further improved SarcasmBERTa (RoBERTa + Custom Multi-Head Attention) model. Table 4.4 shows the ablation research results.

4.2 Results for Mental Health Detection

4.2.1 Ablation Study

An ablation study is done. We measured the performance of our model using accuracy, precision, recall, and F1-score. as shown in Table I, fine-tuned BERT-base and RoBERTa achieved accuracies of 71% and 72%, respectively, while domain-adapted models such as MentalBERT and Men- The RoBERTa model achieved a performance of up to 70%. In contrast, large and zero-shot models, such as BART-large MNLI and MentalLLaMA, comparatively lower accuracy, emphasizing their relative ineffectiveness in this task without task-specific adaptation. The proposed X-MHD model, developed using a DistilBERT-based contextual encoder enriched with knowledge graph representations, achieved the highest test accuracy of 88% while maintaining a parameter-efficient architecture. As shown in Fig. 4.4, the LIME explanation highlights emotionally significant tokens such as “suicidal” and “wont”. While less relevant terms prevent negative influence, exemplifying the interpretability of the proposed model. As shown in Fig. 4.5, the model shows excellent class-wise discrimination, with minor confusion among semantically overlapping categories.

Although other explainability methods such as SHAP and Integrated Gradients have been explored in prior work, LIME was selected in our framework

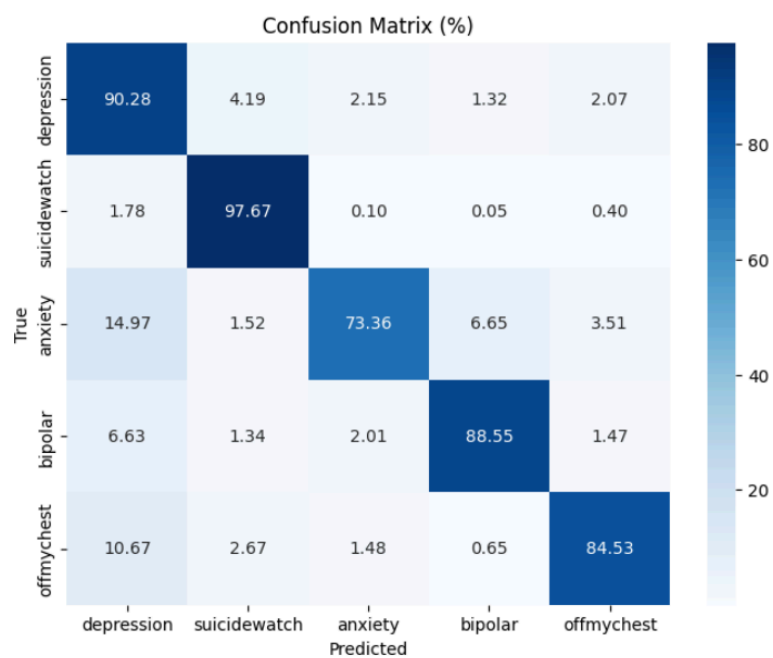


Figure 4.4: F1-score comparison across mental health conditions.



Figure 4.5: LIME-Based Local Explanations for Token-Level Contributions to Predicted Mental Health Category.

as it provides clear local explanations for transformer-based models.

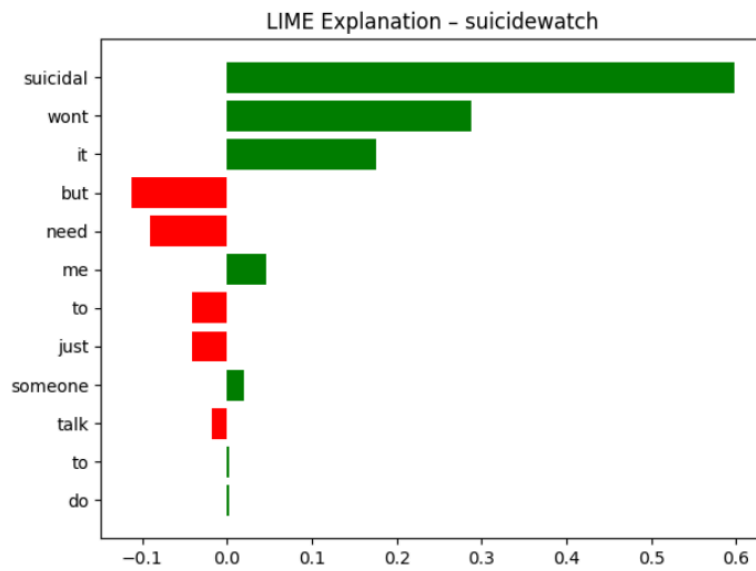


Figure 4.6: LIME-Based Local Explanation for Suicide Watch Prediction, with Token-Level Contributions.

Table 4.3: Performance comparison of the proposed SarcasmBERTa model with baseline and contemporary models on Datasets 3, 4, and 5 using Accuracy (Acc), Precision (Pre), Recall (R), F1-score (F1), and Consistency Loss (CL).

Dataset	Method	Acc	Pre	R	F1	CL
Hindi	TextCNN (Chen, 2015)	0.79	0.73	0.75	0.74	0.053
	Bi-LSTM (Graves and Schmidhuber, 2005)	0.80	0.77	0.78	0.77	0.051
	GloVe (Pennington et al., 2014)	0.81	0.78	0.79	0.78	0.048
	BERT (Devlin et al., 2019)	0.82	0.80	0.81	0.80	0.044
	HumourHindiNet (Kumar et al., 2024)	0.84	0.83	0.84	0.83	0.039
	KFGC-Net (Zhuang et al., 2025)	0.78	0.76	0.77	0.76	0.050
	MMFN (Ou and Li, 2025)	0.81	0.79	0.80	0.79	0.044
	SarcasmBERTa	0.96	0.96	0.96	0.96	0.021
Kota Factory	TextCNN (Chen, 2015)	0.78	0.74	0.76	0.75	0.056
	Bi-LSTM (Graves and Schmidhuber, 2005)	0.82	0.77	0.78	0.77	0.052
	BERT (Devlin et al., 2019)	0.89	0.93	0.86	0.89	0.038
	GloVe (Pennington et al., 2014)	0.90	0.95	0.83	0.89	0.036
	HumourHindiNet (Kumar et al., 2024)	0.91	0.96	0.87	0.91	0.033
	KFGC-Net (Zhuang et al., 2025)	0.82	0.79	0.80	0.79	0.047
	MMFN (Ou and Li, 2025)	0.85	0.82	0.83	0.82	0.041
	SarcasmBERTa	0.96	0.92	0.91	0.92	0.022
Panchayat	TextCNN (Chen, 2015)	0.77	0.75	0.77	0.76	0.058
	Bi-LSTM (Graves and Schmidhuber, 2005)	0.80	0.78	0.79	0.78	0.053
	GloVe (Pennington et al., 2014)	0.85	0.83	0.86	0.85	0.046
	BERT (Devlin et al., 2019)	0.86	0.84	0.87	0.86	0.041
	HumourHindiNet (Kumar et al., 2024)	0.87	0.90	0.84	0.87	0.038
	KFGC-Net (Zhuang et al., 2025)	0.84	0.81	0.82	0.81	0.046
	MMFN (Ou and Li, 2025)	0.87	0.84	0.85	0.84	0.039
	SarcasmBERTa	0.94	0.89	0.91	0.90	0.024

Table 4.4: An ablation study to evaluate the impact of the attention mechanism used in the SarcasmBERTa model.

Model Variant	Correct Rate	Harmonic Mean
RoBERTa (Baseline Fine-tuning)	0.92	0.92
RoBERTa + Attention Layer	0.94	0.94
SarcasmBERTa	0.96	0.96

Table 4.5: Ablation Study of X-MHD

Model Variant	Accuracy
DistilBERT only	78%
DistilBERT + Knowledge Graph	83%
DistilBERT + XAI	80%
DistilBERT + KG + XAI	85%
Full X-MHD (Proposed)	88%

Table 4.6: Summary of Experimental Results on the Test Dataset

Model	Parameters	Accuracy
MentalBERT-base	110 M	69%
MentalRoBERTa	110 M	70%
MentalLLaMA-7B	7 B	59%
<i>Fine-Tuning</i>		
BERT-base	110 M	71%
RoBERTa-base	110 M	72%
<i>Zero-Shot Prompting</i>		
BART-large-mnli	400 M	49%
<i>Proposed Model</i>		
X-MHD	60 M	88%

Table 4.7: Per-Class Performance of X-MHD

Class	Precision	Recall	F1-Score
Depression	0.89	0.87	0.88
Anxiety	0.85	0.83	0.84
Bipolar	0.86	0.85	0.85
SuicideWatch	0.90	0.91	0.90
OffMyChest	0.82	0.84	0.83

CONCLUSION, FUTURE SCOPE AND SOCIAL IMPACT

5.1 Conclusion

The research addressed important challenges associated with contextual ambiguity, multilingual expressions, emotional understanding, and interpretability in social media analysis. For sarcasm detection, the proposed Sarcasm-BERTa framework integrated RoBERTa with Multi-Head Attention mechanisms to capture contextual and semantic relationships in multilingual social media conversations. The model demonstrated superior performance on English, Hindi, and Bengali datasets compared to several traditional and transformer-based baseline approaches. The experimental results showed that the proposed framework effectively identified implicit sarcastic expressions and improved multilingual sarcasm classification accuracy. For mental health detection, the proposed X-MHD framework combined DistilBERT, knowledge graph embeddings, and Explainable Artificial Intelligence techniques for multi-class mental health classification. The framework successfully identified mental health conditions such as depression, anxiety, bipolar disorder, and suicide-related behaviour from textual data collected from online communities. The integration of contextual representation learning and semantic knowledge significantly improved prediction performance and robustness. Furthermore, Explainable Artificial Intelligence techniques including LIME and attention visualization enhanced the interpretability and transparency of the proposed systems by highlighting important words, contextual cues, and semantic relationships responsible for model predictions. These approaches improved the trustworthiness and practical applicability of the proposed frameworks in healthcare-related applications. The proposed frameworks demonstrated the importance of transformer-based contextual learning, attention mechanisms, semantic feature integration, and explainability for improving social media text understanding.

5.2 Future Scope and Social Impact

Future work may focus on extending the proposed frameworks toward multi-modal learning approaches using textual, audio, visual, and facial expression data for improved emotional and psychological analysis. Additional improvements may include integrating lightweight large language models, real-time mental health monitoring systems, adaptive knowledge graph learning, and low-resource multilingual learning for resource-efficient deployment. The incorporation of reinforcement learning and conversational AI systems may further improve user-aware mental health assistance and personalized recommendation systems.

The social impact of this research is significant because social media platforms contain large amounts of emotional and psychological expressions shared by users worldwide. Early identification of mental health risks and emotional distress through automated AI systems can support healthcare professionals, researchers, educational institutions, and online communities in providing timely intervention and awareness. Similarly, accurate sarcasm understanding can improve sentiment analysis, social media moderation, human-computer interaction, and context-aware conversational systems. Therefore, the proposed research has the potential to contribute toward socially responsible, interpretable, and human-centric AI systems for digital mental health and social media understanding.

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