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A HYBRID MODEL FOR CONTEXT-AWARE EMOTION DETECTION USING NATURAL LANGUAGE PROCESSING (NLP) TECHNIQUES

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Abstract

Emotion detection using text has been considered a critical activity in natural language processing (NLP) due to the fact that it is highly diverse in application in areas of social media analysis, customer services, and mental health tracking. The text data in the informal and noisy form can contain delicacy and context sensitive emotional reactions that are incapable of being represented and faithfully mirrored by the customary techniques, such as the lexicon-based and rule-based ones. The hybrid model proposed in this paper is a blend of deep contextual and deep learned representations of transformer-based models such as RoBERTa, with classical lexicon-based features and sequence modelling using Long Short-Term Memory (LSTM). The hybrid model is founded on the benefits of the two approaches to amplify emotion perception in social media texts that are usually featured by the use of informal language, slang, emojis, and ambivalent moods. The model was evaluated based on two publicly available datasets, the Emotion Corpus of Hugging Face (Twitter) and Go Emotions of Kaggle (Reddit) using the assistance of evaluation metrics like accuracy, precision, recall, and F1-score. The result indicated that hybrid model is more effective compared to the single models with the accuracy of 87.3 on the Twitter data and 85.6 on the Reddit data. The findings reveal the practicality of deep learning when collaborated with lexicon based methods in identifying the contextual sensitive emotions, and the solution is sure to apply in the real world situation in dynamism and noise factors.

INTRODUCTION

Identification of emotions in text is very significant in the past several years, and this is largely occasioned by the highly developed nature of online communication and the popularity increased of a social media platform. Emotions are also very essential in human interactions because emotions influence how people communicate and will influence decision making process. They are usually symbolized through the use of language in writing and the reality that one can identify and classify the emotions in written form is critical to many applications, including sentiment analysis, customer service, mental health monitoring, and human-computer interaction (Calderon, 2025). The analysis of emotions expressed in a text is an activity that has been transformed into a fundamental task of Natural Language Processing (NLP) systems with the further advancement of the digital environment. Emotion detection will provide useful data regarding the behavior of the users, the overall mood, and also the emotional well-being and they can make systems sensitive to the mood of the users.

Traditionally, emotion recognition has been performed in the form of rule-based and lexicon-based recognition whereby emotion lexicons have been established beforehand in which words or phrases are correspondingly matched to a specific type of emotion. Coupled with the fact that these techniques are common and popular, occasionally they are insufficient to represent the shapes and subtleties of feelings in writing. In one example, context-specific sarcasm, irony, or context-specific emotions cannot be identified using lexicon-based solutions (Guo, 2022). In many cases, the meaning of a certain sentence cannot be determined without its context, and even words that seem to be neutral or irrelevant by themselves are capable of conveying the most important feelings when they are put in a specific context (Al Maruf et al., 2022). In this way, these traditional methods cannot process the nuances of human emotions and the emotional statements which are latent in the language, to such a large extent.

The limitations have been addressed using deep learning methods. Emotion detection using a deep learning architecture particularly those with recurrent neural networks (RNNs) and transformers have revolutionized the emotion detection research as they include long-range connection and textual contextual representations. These models are able to handle the sequentiality of the language and learn complicated patterns in large volumes of data (Thilakavathy et al., 2024). Transformer models, such as Bidirectional Encoder Representations from Transformers (BERT), have proven to be more effective performers in several NLP tasks, such as detection of emotion, because they can take into consideration long sequence contextual relationship among words (Calderon, 2025). However, despite such a massive success, these models continue to struggle with such noisy and informal text that is so pervasive on social media. Deep learning does not easily recognize emotions in posts in social media written in slang, emojis, mixed feelings, and casual language (Manapure, 2025).

The new researches have outlined the need to combine the force of both the old and the new approach to facilitate the prospects of pinpointing emotions in the complex textual backgrounds. A curious solution to this dilemma is to create hybrid models that have the ability of merging the desirable traits of the two approaches: deep learning and lexicon-based. Lexicon-based methods have good linguistic properties and domain knowledge and deep learning models have good capabilities of capturing complex patterns and contextual information (Poria et al., 2019). Among the hybrid models, which are the combination of these two approaches, emotions, both explicit and smaller, context-specific emotional hints of a text can be better identified, which are in general not identified with the help of traditional methods.

The need to possess context-sensitive emotion recognition systems is even greater upon the background of social media where not only different forms of communication of emotions are observed, but also the idea of emotions is conveyed through various forms. The entries in social media are normally written in an informal language, with abbreviations, emojis, and code-mixed words and phrases, which can have a tremendous impact on the emotional background of the text. This dynamic and diverse form of expression cannot be detected by the traditional models of emotion detection typically based on a fixed word list or rules (Thiab & Mohammad, 2024). In addition, the mere volume of data uploaded to platforms like Twitter and Reddit is also an issue, and emotion processing and categorization model running in real-time is also required. This has generated a necessity to develop models, which can place the context of expressing emotions so that it can classify emotions more strictly in different fields and varieties of languages.

In the paper, one idea is to develop a hybrid emotion detection architecture, i.e. by considering the contextual embedding of transformer models, such as BERT, and the traditional lexicon-based features. The hybrid one will be designed to address the deficiencies of the existing emotion detecting packages by combining the merits of the two approaches. The proposed model will be tested on publicly available data pertaining to the social media platforms, including Twitter and Reddit, by run through the model to detect the level of success in identifying emotions in noisy, informal, and multilingual text. With the incorporation of deep learning and the use of lexicon methods, the model will enable the model to be more precise and robust in emotion detection particularly in relation to dynamic and contextual textual environments. The results of the suggested research will facilitate the work on more effective and adjustable systems of emotion recognising, which could be applied in the interpretation of social media, customer care, and mental research.

In conclusion, it can be stated that emotion detection of a text is a very challenging task, particularly in the case of social media and informal communication. Traditional approaches, despite their assistance, are lesser in terms of their levels of power of capturing the fascination of human hearts. The deep learning models that are based on transformers have reached high potential in emotion detection, but they are not capable of handling noisy and informal language, as well as dependent language. The hybrid system where deep learning is proposed along with lexicon-based one appears to be a promising direction because both approaches benefit one another. The paper is an effort to establish such a hybrid, which would result in more accurate and context-sensitive emotion detection in a social media text. The given research will contribute to the creation of stronger and more reliable models of emotion detection, as the researchers will eliminate the weaknesses of the existing systems to implement it to a wide range of applications.

METHODOLOGY

the approach of the designing and testing the hybrid emotion detecting model that will integrate both transformer-based deep learning models and lexicon-based models. the approach will be covering the data acquisition, the data pre processing, the model architecture, evaluation metrics, and the experiment set-up.

DATA ACQUISITION

The model of a hybrid emotion detector was trained and tested on two publicly available datasets. The first dataset was Dataset I which was the first dataset to be collected on the Hugging Face repository as Twitter posts with six fundamental emotions, such as joy, sadness, love, anger, anxiety, and surprise were identified. Dataset II was acquired at Kaggle and is also known as the Go Emotions dataset and contains over 58,000 Reddit posts, which are classified under 27 possible emotions and the neutral category. Both datasets were chosen due to their applicability to the social media setting and their diversity in the expressions of emotions which offer the most extensive setting to test a performance of the model.

DATA PREPROCESSING

The raw data of the two sets were undergone a comprehensive preprocessing session in order to render them usable in the model. In the preprocessing, the following steps were involved:

Data Cleaning URLs, user mentions (e.g., @username), hashtags and HTML entities were cleaned; they were deemed not to have any relevance to the classification of emotions. There was also the removal of special characters and symbols that were not informative.

Lowercasing: The features were altered to lowercase to achieve the same effect because the variants of capitalization (e.g. Happy vs. happy) were viewed as equal ones.

Tokenization: A tokenizer that is compatible with transformers (e.g., BERT tokenizer) was employed to tokenize the text as subword units, which subunits make up words. This was needed to handle informal languages like slang and emojis.

Stopword Removal:Too common and irrelevant words in the language such as the, is and and, etc were removed so that more meaningful words can be discussed.

Lemmatization: The words were reduced to their root (e.g. crying to cry) and that helped reduce the range of variation of the words in the set and maximized the generalization ability of the model.

Duplication Elimination: All the duplicates or similar duplicates of the tweets were removed to project a representative training data and not to be biased with repeated examples.

MODEL ARCHITECTURE

The proposed hybrid emotion detector model consisted of three major components, i.e. an emotion detecting transformer-based classifier (RoBERTa), a Long Short- Term Memory (LSTM) network and a classical machine learning classifier (Support Vector Machine, SVM). The architecture was designed in a manner that it leveraged on the power of each aspect, therefore, improved performance in categorizing feelings.

Transformer-Based Classifier (RoBERTa): RoBERTa was used in the derivation of deep contextual embedding of every tweet. Transformer model, the connections between the words in a sequence are intercepted and a contextualized sense of the text is obtainable in the transformer model hence it is highly suitable in uncovering minor emotional hints in language.

LSTM Network: LSTM network was fed with the sequence of tokenized embeddings output of RoBERTa and it learned long and sequential relationships in the text. This aspect was what allowed the model to understand the mechanism by which emotions vary across different frames of a tweet and it is crucial to discern emotions in complex and mixed manifestations.

Support Vector Machine (SVM): SVM model has been used in the development of decision boundary with six categories of emotions. The contextual embeddings of the RoBERTa were inputted into SVM and the classification was carried out with a margin on either of the representations of the contextual embeddings produced by the LSTM or sequence-level representations produced by the LSTM and the classification helps to separate the emotions with a better precision.

Ensemble learning was used to gain the outputs of these three models. More specifically, both models had their results added up through a weighted voting scheme, where the results of models were added up based on the performance of the models on the basis of validation. This was a group strategy that was advantageous in that there were more influential models involved in the final decision.

EVALUATION METRICS

The standard metrics adopted to establish the performance of the hybrid emotion detection model were as the following:

Accuracy: The position of the accuracy of the correctly classified tweets of all types of emotion.

Precision: The fraction of correct predictions of every category of emotions among all the predictions identified in the category.

Recall: The proportion of correct prediction of posit of all instances of certain type of emotion of all the actual instances of that type of emotion.

F1- Score: The harmonic average of the precision and the recall that provides a balanced score of the model on the precision and the recall.

The measures were calculated in relation to all forms of emotions (joy, sadness, love, anger, fear, and surprise) and the functioning of the entire model.

EXPERIMENTAL SETUP

They were conducted in an experimental setting that was controlled with a machine that had the necessary computation resources to run the deep learning models. The information was separated into three categories, i.e. training, validation and testing. The models were trained with the training set, then fine-tuned with the validation set and the most suitable hyperparameters were selected, and the results of the last model were evaluated with the test set.

Adam optimizer was utilized and the learning rate was set to 0.0001 and the number of epochs was to a fixed one with early stopping by validation accuracy in order to make sure that the model was not overfitting. The models (RoBERTa, LSTM and SVM) were first run individually, as various hybrid models (SVM+RoBERTa, SVM+LSTM, RoBERTa +LSTM, and SVM+RoBERTa +LSTM ensemble) and in various configurations. The results of these experiments were correlated to make a conclusion on the optimal combination of models which would result in high performance.

RESULTS

This chapter presents the result of the tests conducted to examine the behavior of the hybrid emotion detection model suggested. The hybrid is the product of transformer based embeddings of RoBERTa, sequence modeling using LSTM, and traditional machine learning classifier such as SVM. It was also observed that the hybrid model has been compared against the individual deep learning models (RoBERTa and LSTM) and the traditional machine learning models (SVM) upon different measures of evaluation, including accuracy, precision, recall, and F1-

score. The experiments have been conducted on two publicly available datasets, including Emotion Corpus of Hugging Face (Twitter dataset) and Go Emotions dataset of Kaggle (Reddit dataset).

5.1 PERFORMANCE COMPARISON BETWEEN MODELS.

The data sets were separated into training set, validation set and testing set to evaluate the performance of the models. The results of each of the models of RoBERTa, LSTM, SVM and the hybrid models are presented in Tables 1, 2 and 3 below. Accuracy, precision, recall and F1-score of each of the six emotion categories (joy, sadness, love, anger, fear and surprise) are the measures of the evaluation.

Table 1: Performance on Emotion Corpus (Twitter Dataset)

Model	Accuracy	Precision	Recall	F1-Score
RoBERTa (Transformer)	81.2%	0.79	0.78	0.78
LSTM	77.5%	0.74	0.73	0.73
SVM	72.9%	0.71	0.70	0.70
Hybrid (SVM + RoBERTa)	85.4%	0.83	0.82	0.82
Hybrid (RoBERTa + LSTM)	84.7%	0.82	0.81	0.81
Hybrid (SVM + RoBERTa + LSTM)	87.3%	**0.85**	**0.84**	**0.84**

Table 2: Performance on Go Emotions Dataset (Reddit Dataset)

Model	Accuracy	Precision	Recall	F1-Score
RoBERTa (Transformer)	79.6%	0.78	0.77	0.77
LSTM	74.8%	0.72	0.71	0.71
SVM	69.1%	0.68	0.67	0.67
Hybrid (SVM + RoBERTa)	83.3%	0.81	0.80	0.80
Hybrid (RoBERTa + LSTM)	82.5%	0.80	0.79	0.79
Hybrid (SVM + RoBERTa + LSTM)	85.6%	**0.84**	**0.83**	**0.83**

Table 3: Performance Comparison Between Hybrid Models

Hybrid Model	Accuracy	Precision	Recall	F1-Score
Hybrid (SVM + RoBERTa)	84.4%	0.82	0.81	0.81
Hybrid (RoBERTa + LSTM)	83.6%	0.81	0.80	0.80
Hybrid (SVM + RoBERTa + LSTM)	86.5%	**0.84**	**0.83**	**0.83**

5.2 MODEL PERFORMANCE ANALYSIS

The results demonstrate that the hybrid models are superior to the individual ones in all measures of evaluation, namely in accuracy, precision, recall and F1-score. The hybrid model of SVM, RoBERTa and LSTM achieved the best performance in both datasets and its accuracy was 87.3 in Emotion Corpus (Twitter dataset) and 85.6 in Go Emotions (Reddit dataset).

RoBERTa (Transformer): RoBERTa is another transformer, and it was the most accurate of the single models with an accuracy score of 81.2 and 79.6 on Twitter and Reddit datasets, respectively. However, it was pointed out to have been weak in the categorization of emotions to certain categories such as fear and sadness since accuracy and recall scores were lower compared to the hybrid models.

LSTM: LSTM model had poor performance compared to RoBERTa and SVM in both datasets and its performance had an accuracy rate of 77.5 percent and 74.8 percent in both datasets respectively. In spite of the fact that LSTM is especially efficient in terms of the ability to consider the temporal dependencies, the inability to consider more complex contextual relations in the manner RoBERTa did undermined its performance.

SVM: SVM model is the least accurate with the lowest accuracy scores of 72.9% and 69.1 as an independent model. Although it is simple and efficient, SVM has failed to produce sequential and contextual relationships which are valuable in the emotion detection exercise in social media text.

Models Hybrid Models: The hybrid models were doing fairly well compared with the modelling models. SVM+RoBERTa was estimated to achieve an accuracy of 85.4 and 83.3 on the Twitter and the Reddit datasets, respectively, and RoBERTa + LSTM was estimated to have almost identical scores though quite impressive. The most successful hybrid one was SVM + RoBERTa + LSTM, which had the highest accuracy (87.3% on Twitter and 85.6% on Reddit) and precision (0.85) and recall (0.84) and F1-score (0.84 and 0.83, respectively). These results indicate the alignability of the benefits of deep learning model (RoBERTa and LSTM) and the conventional machines learning classifiers (SVM).

5.3 ERROR ANALYSIS

Still, the hybrid model had the highest level of accuracy, but there were some misclassifications observed, especially with such emotions as fear or surprise. These feelings were sometimes confused or rather confounded with each other either in cases where the textual representation was not emphatic or a combination of other emotions. The nature of errors was also uncovered by exploring the nature of errors that occurred that revealed that the model was experiencing problems with the identification of emotions in very short texts which is common in social media posts such as twits. The use of emojis, slangs, and informal language was also an issue with the model, even though the hybrid approach was used.

5.4 HYBRID APPROACH COMPARATIVE ADVANTAGE.

The results allow concluding that the hybrid model with the SVM + RoBERTa + LSTM was a more legitimate and plausible solution to the problem of emotion identification than any single model. The bi-hybrid process using the benefits of contextual embeddings (RoBERTa), sequential connections (LM), and margin-based decision margins (SVM) performed well in the retrieval of explicit and implicit emotional cues in social media text. The implication of this observation is that new emotion detection systems have to consider hybrid methods to enhance their performance, and especially in noisy and less formal and multiple lingual environments, like social media.

The usefulness of hybrid models in detecting emotions in the text of social media is proven in the experiments of the proposed study. The combination of the SVM and RoBERTa and LSTM models were better than the individual models of the deep learning and machine learning since it was discovered to possess the highest competence to recognize overt and subtle emotional expressions. The results of the paper can be applied to the more realistic and context-specific emotion detection models development and implemented to the social media analysis, customer care, and mental health monitoring.

DISCUSSION

The research results prove the effectiveness of the proposed hybrid emotion recognition model that combines deep learning and traditional machine learning algorithms to increase the recognition of emotions in text on social media. The hybrid model, particularly SVM + RoBERTa + LSTM performed better with regard to accuracy, precision, recall and F1-score compared to single models. The findings of this paper are giving several hints on the challenges and opportunities of emotion recognition in noisy and informal text and the possibilities of the hybrid solutions to the challenges.

One of the strengths of the hybrid model is the possibility of integrating the situational knowledge of the transformer-based models like RoBERTa with sequential pattern recognition of LSTM and margin-based decision boundary of

SVM. RoBERTa transformer-based model is most proficient in encoding long-range association and contextual linkages of words and this is needed in the identification of emotions in dynamic complex texts like social media posts. However, despite RoBERTa being more precise than the rest of single-user models, it was not perfect in its performance particularly when it comes to less apparent emotions such as fear and sadness. This demonstrates the inherent weakness of deep learning models that in some instances cannot identify emotions on ambiguous or delicate expressions, especially when the emotional indicators are not explicitly elicited.

The LSTM model, on its part, did not fare well alone, failing to provide the global picture, as RoBERTa. However, in the hybrid approach using RoBERTa, LSTM may contribute to improving the ability of the model to understand the sequential and emotional variation by a tweet which improved the overall performance. However, SVM model, even though it was also the lowest of the single models, and the set of models, gave helpful decision boundaries where differentiating between different emotions was done using them. The hybrid model of SVM + RoBERTa + LSTM came in handy to balance the benefits of both of them and introduce more specific and context-sensitive system of emotion detection.

The other interesting conclusion of this paper is the application of the noisy and informal text in detecting emotions. The use of informal language, slang, emojis, ambivalent feelings and similarity feature of social media like twitter and Reddit are highly challenging to be identified with emotion detecting systems due to the language they employ. Deep learning models are complicated but often cannot handle such characteristics. The ability of the hybrid model to handle the informal language and noisy data, particularly the feature of using lexicon and deep learning in particular, played a major role in improving performance. The use of emojis, hashtags and slang to express emotion is a common practice that cannot be effectively represented by the standard machine learning models. Having these features integrated into the preprocessing of the model and its architecture, the hybrid approach proved to be efficient in processing a multitude and a variety of social media text that is noisy.

The other critical observation that the results indicate is the need to have models that are able to generalize inter-domain and inter-language. The success of the hybrid model in the case of the Twitter and Reddit data which is a reflection of a separate social media space is a sign of its strength. However, it can be refined, in particular, when it comes to processing code-mixed or multilingual data. The models that are available like the hybrid model, do not tend to cope effectively with texts that comprise over one language or blend of feelings. As the world is becoming increasingly globalized and diverse in digital communication, it becomes necessary to model the future of the emotion detection systems and develop a model that can handle these problems.

Additionally, although the hybrid model was highly accurate, it did not exclude misclassifications, in particular, with regard to such emotions as fear and surprise. This tends to be the issue with the emotion detecting systems as there is a chance that the expression of emotions can be subtle, mixed or ambiguous. To get rid of this, the application of other features such as audio or visual feature, which has been observed to enhance the ability to detect emotion in multimodal systems, could be ascertained in future studies (Kim et al., 2023). This may result in an increase of accuracy and strength in the model of detecting emotions in cases where multimodal data will be included specifically in those cases where text messages will not be sufficient to capture the emotion.

In conclusion, the given hybrid emotion detection model proves that there is a possibility of positive changes in promoting the understanding of emotions in the context of noisy, informal, and multilingual social media texts. The hybrid solution that combines the strength of deep learning model and a traditional machine learning classifier will offer a superior and more precise and contextual-driven method of emotion detection than the existing methods do. Despite the fact that the model has proven to be far more effective than the individual models, there are still problems that it is required to resolve, i.e. the processing of mixed or ambiguous affects, and lastly the processing of multilingual and code-mixed texts. The additional research will be oriented to developing the model better to be able to correct those problems in a more effective manner, perhaps, by incorporating the multimodal data to make the emotion detection system even more efficient.

CONCLUSION

The paper introduces a twofold emotion detection model, a combination of the power of transformer-based network (RoBERTa), sequence modeling and LSTM, and traditional machine learning algorithms (SVM) to strengthen the classification of emotions in social media text. These experimental results showed that the hybrid model was far superior to the individual deep learning and machine learning model in terms of accuracy, precision, recall, and F1-score. SVM + RoBERTa + LSTM model performed better in the two datasets achieving an accuracy of 87.3 percent and 85.6 percent in the twitter dataset and Reddit dataset respectively. Such a lexicon based feature coupled with deep learning helped the model to be more efficient in handling informal languages, slangs, emojis and mixed emotions, which form the posts in the social media. Despite the most positive results, the issue of tackling sensitive emotions and code-mixed or multi-linguistic texts has been facing its challenge, which, in its turn, can be enhanced, as the provided model can be enhanced as well. In the present, the work on the ways to mitigate these limitations will continue and might include the implementation of multimodal data to enable the emotion detection systems to become more resistant and adapted to diverse and constantly evolving digital environments.

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