Multimodal Code-Mixed Tamil Troll Meme Classification using Feature Fusion

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Abstract

Memes became an important way of expressing relevant idea through social media platforms and forums. At the same time, these memes are trolled by a person who tries to get identified from the other internet users like social media users, chat rooms and blogs. The memes contain both textual and visual information. Based on the content of memes, they are trolled in online community. There is no restriction for language usage in online media. The present work focuses on whether memes are trolled or not trolled. The proposed multi modal approach achieved considerably better weighted average F1 score of 0.5437 compared to Unimodal approaches. The other performance metrics like precision, recall, accuracy and macro average have also been studied to observe the proposed system.

1 Introduction

Social Media is a technology where people share information, idea and their opinions to the virtual group of people. These contents uses internet to reach the people via electronic medium, which includes photos, videos, and textual information (Chakravarthi and Muralidaran, 2021; Chakravarthi et al., 2022). These electronic social media contents are accessed through computers, mobiles, tablets via the web based applications (Hande et al., 2022; Shanmugavadivel et al., 2022; Subramanian et al., 2022). Government keep an eye on the conventional media contents, because the information shared in conventional media are monitored for trolled contents (Chakravarthi, 2020, 2022b,a). But in case of social media there is no strict laws or methodologies to monitor the internet contents.

One of the most important way of sharing our thought is either via text messages or via images. There are so many contributions for social media contents like text, emojis, info graphics, charts and photographs. In this, photographs and texts plays a key role. Meme is an element of behaviour imitation passed from an individual to another. Meme was first coined by British evolutionary biologist Richard Dawkins in 1976 (ric). It is an idea to mutate, replicate or imitate others behaviours to pass an information. It is an art of writing human creativity.

Memes with text and images could be detected for trolled or not trolled. Visual question answering, image captioning (Biswas et al., 2020) and identifying the images are categorised as classification problem that depends both on the individual inputs. This type of classification task is portrayed in Troll meme classification in Tamil (Beltrán et al., 2021) (Suryawanshi et al., 2020). This task focuses on memes as trolled or not trolled. The idea of trolled is determined by the text and image interaction as shown in Figure 1-2.

Authors handled the multi modal input data for different applications such as Hateful Meme detection (Evtimov et al., 2020) and adversarial Meme detection (Lippe et al., 2020) . Particularly the Figure 1 shows that the event happened in recent times with popular occurrences/offensive texts are get trolled. But in case of 2 is not an recent time activity happened does not contain any harm or offensive messages that are not get trolled.

Meme is a good imitation of a real world problem. Here the task on Troll meme classification in Tamil is a task of classifying the memes into hate and non hate images. Troll is nothing but a offensive message or disruptive message in the social media. The language mentioned in the task is Tamil. For the text memes, corresponding image memes also given. By using the texts and the images, the proposed system need to classify whether the meme is trolled or not. The evaluation metric from the data set is taken as weighted F1 score.

In this research, we have defined the research

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Figure 1: Example image for Troll meme

Figure 2: Example image for Non Troll meme

Figure 1 is trolled and Figure 2 is not trolled image. Figure 1-Enga vote ah eppa sir enuvinga which is in tanglish is transliterated as *"when will you count our vote sir"*, Figure 2- ungala maari oru friend kadaikka naan romba koduthu vechirukkanu in tanglish is transliterated as *"it would be great to have a friend like you..."*

questions and the same have been addressed in the next upcoming sections. Research Question 1: To study the performance of the pretrained word embedding like GloVe for transliterated content. Research Question 2: Analyse the performance of the GloVe embedding with other language based pretrained models Research Question 3: To study the performance of the system with the Deep learning architectures with GloVe embeddings. To solve the research questions, extensive literature study have been conducted and reported.

This section describes about the introduction and Section 2 and 3 talks about the related works and methodologies used in the classification task. Section 4 describes the results and discussion and last section deals with Conclusion of the paper.

2 Related Works

Multimodal representation have recently gained good attention due to the uni modals (Suryawanshi et al., 2020) poor performance on the applications such as image captioning (Biswas et al., 2020), visual reasoning (Ye, 2021) , memes classification and Visual question answering (Cadène et al., 2019). Multimodal task involves visual and language understanding between the two Unimodalities. Maximum works carried on Multimodal systems have either one is Late fusion (LF) (Snoek et al., 2005) or Early fusion (EF) (Sai et al., 2022). The other fusion techniques are Hybrid multimodal fusion, Model-level fusion, Rule-based fusion, Classification-based fusion, Estimation-based fusion are reported in the literature survey (Poria et al., 2017). Late fusion process involves two unimodal system independently till before the last layer and fuse the their decisions for further processing. Early fusion approach uses two modalities with complex approaches within the model architectures. Early fusion of the features provide better representation for further processing in accomplishing the task. Some of the steps are followed in NLP type of task are pre-processing , feature engineering, and dimensionality reduction. Preprocessing involves stop word removal, tokenization, spelling correction, noise removal, remove numbers, stemming and lemmeatization. For English memes (Suryawanshi et al., 2020) these types of pre processings are applicable, but in case of non English memes some other type of pre processing be used to clean the input data. Applied stop word removal and special characters removed on transliterated dataset content. Feature engineering is used to extract useful features from the input data. Some of the feature engineering word embedding approaches are GloVe, Word2Vec, Ngram and Term frequency and Inverse Document frequency. Dimensionality reduction technique used to reduce the dimensionality of the large data sets into a smaller data set which may contain the most important features from large data set. For social media comments (Kannan et al., 2021; Soubraylu and Rajalakshmi, 2021a; Rajalakshmi et al., 2021), different transformer based approaches and attention based approach are proposed. Many researchers have implemented classifiers such as KNN, Naive Bayes,SVM and Ensemble classifiers (Rajalakshmi et al., 2022c; Rajalakshmi and Reddy, 2019).

Recently Deep Learning (DL) methods such as RNN, CNN and transformer models (Devlin et al., 2018; Liu et al., 2019; Lan et al., 2020; Gurari et al., 2020), BiLSTM-CRF(Rajalakshmi et al., 2022b) and hybrid convolutional bidirectional recurrent neural network for sentiment analysis(Soubraylu and Rajalakshmi, 2021b) attains better results compared to Machine learning models due to ability to model complex representations inside the data.

Image classification on meme classification starts with the pre processing steps like resize the image, noise removal, RGB2Gray scale conversion and segmentation process. After pre processing feature extraction involves color extraction, texture extraction, shape and deep feature extraction. For short text classification task (Rajalakshmi et al., 2020a), proposed CNN with Bi-GRU on Open Directory Project (ODP) dataset and obtained 82.04% accuracy.

(Ganganwar and Rajalakshmi, 2022; Rajalakshmi et al., 2021, 2023) studied the performance of transformers on the code-mixed social media contents. (Ganganwar and Rajalakshmi, 2022) proposed translation based offensive content identification on Tamil text using pretrained word embedding. MuRIL pretrained embeddings were used by the translated content for classification. In (Rajalakshmi and Agrawal, 2017), authors proposed relevance based metric for code-mixed language by using statistics based approach. (Rajalakshmi et al., 2021) proposed transformer based approach for identification of offensive content on social media Tamil comments. In (Soubraylu and Rajalakshmi, 2022), the authors proposed transfer learning approach for movie review by using Bidirectional Gate Recurrent Unit(BGRU). The features from BERT embeddings are used as features for transfer learning approach. (Rajalakshmi et al., 2023) proposed MuRIL based approach for YouTube comments for offensive content identification. (Ravikiran et al., 2022) created dataset for offensive span identification for Code-Mixed social media Tamil contents. (Rajalakshmi, 2014, 2015; Rajalakshmi and Aravindan, 2018; Rajalakshmi and Xaviar, 2017; Rajalakshmi et al., 2020b) Traditional machine learning algorithms and text embedding methods (Rajalakshmi et al., 2018) have been proposed on short text classifications. Transformer based approach (Rajalakshmi et al., 2022a) and XGBoost (Sharen and Rajalakshmi, 2022) based approaches were used on depression detection using signs. Aspect-based approach (Ganganwar and Rajalakshmi, 2019) is studied on sentiment analysis.

Most of the image classifier models uses Convolutional Neural Network (CNN) architecture for feature extraction, which automatically extracts the features from the data inputs. MobileNetV2 (Sandler et al., 2018) pre-trained model uses these automatic feature extraction of deep learning model with depth wise convolution and point wise convolution for reducing the parameters. In our Multimodal classifier approach, the proposed system used CNN with Bidirectional Long Short Term Memory (Bi-LSTM) as text classifier and MobileNetV2 as image classifier for troll meme classification with multimodal approach. A detailed experimental study has been conducted to explore the role of CNN, Bi-LSTM and combination of both. CNN works well for short text analysis in English (Rajalakshmi et al., 2020a). To explore the role of CNN for our application we adapted the same to our approach. MobileNetV2 is very effective feature extractor for image classification problems better than VGG and ResNet. So we have adopted both to our proposed architecture.

3 Methodology

3.1 Data Set

The data set provided for the Troll Meme classification (Suryawanshi and Chakravarthi, 2021) with 2300 as training data with text and image inputs and 667 as test set inputs. 2100 inputs are taken for training and 200 for validation process. Here the data set is splitted into around 80% for training and 20% for testing. For validation set 9% of the data taken from training set. Data set contains trolled/not trolled texts and images of trolled/not trolled images and their corresponding labels. Figure 1 is trolled image with text as **"Enga vote ah eppa sir enuvinga"** which is in tanglish is transliterated as **"when will you count our vote sir"** and Figure 2 is not trolled image with text as **"ungala maari oru friend kadaikka naan romba koduthu vechirukkanu"** in tanglish is transliterated as **"it would be great to have a friend like you..."**

Table 1: Data Set Description

Data Set	Troll	Not Troll	Total
Training	1182	918	2100
Validation	100	100	200
Testing	395	272	667

3.2 Architecture

Deep learning architectures CNN and Bi-LSTM are used for text classification, which uses CNN for feature extraction and Bi-LSTM in both the directions to capture the sequence of the text representations. LSTM (Long Short Term Memory) captures the next sequence in unidirectional way.

but in case of Bi-LSTM, it is used to find the next sequence of words in both the directions. CNN used to capture the important features from the text data and the same is passed to Bi-LSTM to maintain the sequence of the statement. Meme's texts contains Tamil words transliterated in English. Syntactic and semantic meaning of Tamil words in native languages are completely different than English, but in case for Meme's, the messages are represented in Tamil, English and Tanglish (Tamil+English) representations are transliterated and represented in English . The dataset with image may contain Tamil texts, but the data set released with transliterated format of the Meme's texts.

GloVe (Global Vectors for word representation) vector with 50 dimension is used for obtaining vector representations of input sequences. We have tried other GloVe embedding dimensions such as 50, 100, 200. In addition to GloVe embedding, we have tried with IndicBERT and mBERT approaches and achieved 0.5379 and 0.5219 respectively. 50 dimension shown better performance on the Meme's text architecture. This is used to get the global word occurrence statistics from the corpus. Maximum length of the sequence is set as 150. The architecture followed with Input layer, embedding layer, CNN, Bi-LSTM. The sequence information from Bi-LSTM is given as input to Global Average pooling layer and Max pooling layer separately and concatenated towards dense layer followed by dropout and dense layer. Number of units in the Bi-LSTM is 200 units, CNN with kernel size as 3, filter size 30 are selected with hyper parameter tuning. Sigmoid activation function is used since it is a binary classification.

Table 2: Meme Classification based on Text

Class	Precision	Recall	F1
Not Troll	0.4324	0.3529	0.3887
Troll	0.6045	0.6810	0.6405
M.Avg	0.5185	0.5170	0.5146
W.Avg	0.5343	0.5472	0.5378

For Image classification, pretrained image classification model MobileNetV2 (Sandler et al., 2018) is used, which uses expanded representations in light weight depth wise manner. It uses convolution layers to filter out the features from the intermediate layers of the model. It removes non linearities to represent the features of the input data. The extracted features from the meme images and the extracted features with text features are fused for further processing. Images in the meme classification are with input size of 150. Figure 1 is a trolled image contains trolled messages in the text form. But in case of not trolled image (Figure 2) are only expressions, that may or may not contain the trolled message. So troll meme classification in Tamil is not like a regular image classification problem. With the help of text only input does not enough to develop the system. With the help of images and text can develop better system for troll meme classification. Early fusion is applied on multi modal data inputs build a multi modal classifier. concatenated features are given to dense layer for final classification.

4 Results and Discussion

Table 2, shows the classification of the text input with the Deep learning approach of CNN with Bi-LSTM model which achieved a weighted F1 score of 0.5378 for text input data. The model trained for 25 epochs and obtained a training accuracy of 0.8905 and loss of 0.3054. The validation set obtained a accuracy of 0.6714 and loss of 0.7057 on Meme's texts with a batch size of 128 and sigmoid as activation function. The recall score for Troll Meme text is shown with 0.6810 score, because the model has identified around 68% of the Troll text correctly. The precision score shown as 0.6045 for the Troll text. The macro average score shows an overall performance of the system with each metrics.

Table 3: Meme Classification based on Image

Class	Precision	Recall	F1
Not Troll	0.4202	0.4743	0.4456
Troll	0.6028	0.5494	0.5748
M.Avg	0.5115	0.5118	0.5102
W.Avg	0.5283	0.5187	0.5221

Image classification on troll meme achieved a weighted average F1 score of 0.5221 and precision as 0.5283 and recall as 0.518 on troll image classification for the MobileNetV2 architecture. This image classification model, which uses pre-trained model of MobileNetV2 for feature extraction in depth wise and point wise convolutions. From Table 3, trolled images are classified better than not trolled images. because of the meme images may not contain same set of pattern on images for feature extraction. Obtained a training accuracy of 0.9810 and validation accuracy of 0.9652. The same model obtained a loss of 0.0612, 0.1760 on training set and validation set respectively. The table shown overall Troll classified images with 60% from the test set.

Table 4: Meme Classification based on Multimodal

Class	Precision	Recall	F1
Not Troll	0.4402	0.3787	0.4071
Troll	0.6097	0.6684	0.6377
M.Avg	0.5249	0.5235	0.5224
W.Avg	0.5406	0.5502	0.5437

Table 5: Comparison Result on Multimodal

Multimodal	Result
BiGRU+CNN	0.4 (Huang and Bai, 2021)
Bert+ViT	0.47 (Hegde et al., 2021)
Bi-LSTM+CNN	0.525 (Hossain et al., 2021)
Our Approach	**0.5437**

Early Fusion on Multimodal classification achieved 0.5437 weighted average F1 score on troll memes, which is a 1% increase in the performance of Unimodal classifications. Table 4, shows the results of Multimodal meme classification results. We have conducted 4 fold and 5 fold cross validation for text contents and image contents. The CNN-Bi-LSTM approach obtained overall cross validation of 71.24% and 73.81% on 4 fold and 5 fold training sets. The same has been conducted to test and obtained 54.46% and 54.27% for 4 fold and 5 fold respectively. The same cross validation has been conducted on MobileNetV2 to verify the system performance. 4 fold cross validation obtained 55.74% and 59.22% on train set and test respectively. 5 fold cross validation on train set obtained 55.87% and 59.22% on test set respectively. From this the obtained results using the full training set is consistent with the cross validation score performance.

From Table 5, the comparison of our approach with other approaches on the same data set has been discussed. (Huang and Bai, 2021) proposed fusion approach with Bidirectional GRU (BGRU) for Text classification and Convolutional Neural Network (CNN) for image classification and obtained 0.4 of F1 score. (Hegde et al., 2021) used the same data set and obtained 0.47 using Bidirectional Encoder Representations from Transformers (BERT) for Text classification and Vision Transformer (ViT) for Image classification with Early fusion. (Hossain et al., 2021) used Bi-LSTM for meme Text classification and CNN for Image classification and obtained 0.525 F1 score. From the above mentioned results our approach on Multimodal Meme classification obtained a F1 Score of 0.5437 using CNN-Bi-LSTM for Text classification and MobileNetV2 for image classification. Sequence features are extracted using Bi-LSTM and other features are extracted using CNN in trolled messages. pre-trained MobileNetV2 architecture used to extract the features from Trolled image data sets. Both features are concatenated to form a new feature vector space and classified as multimodal analysis. By this, Multimodal classifiers results are better than Unimodal classifiers on text and image inputs.

From our results, the recall value for Troll text and images shown higher results compared to precision on all the unimodal approaches. Because all the images on the data set contains shown very few false negatives. It means that troll categories are classified almost correctly. We need to concentrate more on Non troll contents of both text and images to improve the performance of the system. On comparing the results of the recall on unimodal and Multimodal approach, the image classifier classified more Troll images in terms of True category. For Non troll category all the modals have higher precision score than recall score.

Statistical significance test, Fried man test is conducted for our proposed architecture with other two unimodal approaches. Null Hypothesis h0 and different alternate hypothesis H1 is defined and computed the score. For 10 instances and level of significance as 0.01 is observed on Fried table and obtained Fr as 9.60. We have populated the table with respective rankings and calculated the score as 72.9. This is greater than 9.60 of table value. So we can accept the alternate hypothesis. This assessment tool is used the test the performance of the proposed system with other systems.

5 Conclusion

Combination of sequence based model and pre-trained image model showed better performance. CNN-Bi-LSTM classifier on text input and MobileNetV2 on image input combination obtained some better performance on multimodal approach.

The GloVe embedding performance on troll classification shown better performance with Deep Learning architectures. In order to obtain better result, the multimodal approach shown some better performance than the unimodal approaches. The performance metrics weighted F1 score is chosen to balance the results on the both class labels. Weighted average on meme classification gives important to both the classes. By using Multimodal classification approach on memes attained a result of 0.5437 weighted F1 score. The performance of the Multimodal classifier can be improved with more number of input data and feature extraction on images. The dataset is created on low-resource language Tamil and the cultural adaptation details can be considered for future scope.

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