CUET-NLP@DravidianLangTech-ACL2022: Investigating Deep Learning Techniques to Detect Multimodal Troll Memes

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Abstract

With the substantial rise of internet usage, social media has become a powerful communication medium to convey information, opinions, and feelings on various issues. Recently, memes have become a popular way of sharing information on social media. Usually, memes is visuals with text incorporated into them and quickly disseminate hatred and offensive content. Detecting or classifying memes are challenging due to their region-specific interpretation and multimodal nature. This work presents a meme classification technique in Tamil developed by the CUET NLP team under the shared task (DravidianLangTech-ACL2022). Several computational models have been investigated to perform the classification task. This work also explored visual and textual features using VGG16, ResNet50, VGG19, CNN and CNN+LSTM models. Multimodal features are extracted by combining image (VGG16) and text (CNN, LSTM+CNN) characteristics. Results demonstrate that the textual strategy with CNN+LSTM achieved the highest weighted f_1-score (0.52) and recall (0.57). Moreover, the CNN-Text+VGG16 outperformed the other models concerning the multimodal memes detection by achieving the highest f_1-score of 0.49, but the LSTM+CNN model allowed the team to achieve 4^{th} place in the shared task.

1 Introduction

The **Meme** refers to an element of a culture or system of behaviour conveyed from one individual to another by imitation or other non-genetic actions. Memes appear in various formats, including but not limited to photographs, videos, tweets, and have a growing influence on social media communication (French, 2017; Suryawanshi et al., 2020b). Images with embedded text are the most widely used form of memes. Memes facilitate transmitting ideas or feelings spontaneously. Posting and sharing memes have recently become a popular way of disseminating information on social media since memes can propagate information humorously or sarcastically (Ghanghor et al., 2021a,b; Yasaswini et al., 2021). Propagation of malicious memes and other related activities via memes such as trolling, cyberbullying is rapidly rising (Chakravarthi, 2020; Chakravarthi and Muralidaran, 2021). The implicit meaning of the memes, presence of ambiguous, humorous, sarcastic terms, and usage of attractive, comical, theatrical images have made meme classification even more complicated (Kumari et al., 2021; Chakravarthi et al., 2021). For example, in Figure 1, text and image individually exhibit no means of attack. However, considering both modalities, it insults the persons by directing the age gap in their marriage. To facilitate research in this arena, this work presents our system to classify multimodal troll memes for the Tamil language.

Tamil is a member of the southern branch of the Dravidian languages, a group of about 26 languages indigenous to the Indian subcontinent. It is also classed as a member of the Tamil language family, which contains the languages of around 35 ethno-linguistic groups, including the Irula and Yerukula languages (Sakuntharaj and Mahesan, 2021, 2017, 2016; Thavareesan and Mahesan, 2019, 2020a,b, 2021). Tamil is an official language of Tamil Nadu, Sri Lanka, Singapore, and the Union Territory of Puducherry in India. Significant minority speak Tamil in the four other South Indian states of Kerala, Karnataka, Andhra Pradesh, and Telangana, as well as the Union Territory of the Andaman and Nicobar Islands (Bharathi et al., 2022; Priyadharshini et al., 2022). It is also spoken by the Tamil diaspora, which may be found in Malaysia, Myanmar, South Africa, the United Kingdom, the United States, Canada, Australia, and Mauritius. Tamil is also the native language of Sri Lankan Moors. Tamil, one of the 22 scheduled languages in the Indian Constitution, was the first to be designated as a classical language of India (Anita and Subalalitha, 2019b,a; Subalalitha and Poovam-

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mal, 2018; Subalalitha, 2019; Srinivasan and Subalalitha, 2019; Narasimhan et al., 2018).

We experimented with several deep learning models to extract visual and textual features. After investigating the outcomes, an early fusion approach is employed to combine the features from both modalities. The results indicate that the textual models acquired higher f_1-score compared to the visual and multimodal counterparts.

Figure 1: A sample Troll meme

2 Related Work

Over the past few years, trolling, hostility, offensive, and abusive language detection from social media data have been extensively studied by NLP professionals (Kumari et al., 2021; Hossain et al., 2021; Mandl et al., 2020; Sharif et al., 2021a). The majority of these researches were carried out considering only textual information (Li, 2021; Sharif et al., 2021b). However, a meme's existence can be found in an image and text embedded in an image. Few researchers have investigated both textual and visual features of memes to classify trolls, offences and aggression. Sadiq et al. Sadiq et al. (2021) developed and compared several models to identify cyber-trolling tweets. Models include the Multi-Layer Perceptron (MLP) with TF–IDF features, MLP with word embedding, and two deep neural networks: CNN with LSTM and CNN with BiLSTM. Results exhibited that MLP with the TF–IDF features-based model outperformed other models with an accuracy of 0.92. Kumari et al. (2021) proposed a hybrid model in which the image features are retrieved using pre-trained VGG-16, and the textual features are extracted through a layered CNN model. These features are optimized using the binary particle swarm optimization technique (BPSO), contributing to a weighted f_1-score of 0.74. Suryawanshi et al. (2020a) created a multimodal dataset of 743 offensive and not-offensive memes from the 2016 presidential election in the United States. To merge the multimodal characteristics, they used an early fusion method. The combined model received a 0.50 f1-score, but the text-based CNN model outperformed it with a 0.54 f1-score. Most previous studies focused on categorizing memes based on unimodal data: text or image. However, this work considers detecting memes from multimodal data: text and image in Tamil. Pranesh and Shekhar (2020) proposed a multimodal framework (MemSem) consisting of VGG19 for image features and BERT for text features. MemeSem achieved a better result than all unimodal and multimodal baselines with 67.12% accuracy. Gomez et al. (2020) developed a multimodal hate speech dataset containing images and corresponding tweets. The results indicate that the multimodal model (CNN+RNN) was not outperformed the textual model. Bucur et al. (2022) employed a 3-branch network for sentiment analysis. They used EfficientNetV4 and CLIP to extract image features, while a sentence transformer was used to get the text features. The system achieved a weighted f_1-score of 0.5318 with the CORAL loss function.

3 Task and Dataset Descriptions

A troll meme is an image with embedded offensive or sarcastic text which degrade, provoke, or offend a person or group (Suryawanshi et al., 2020b; Gandhi et al., 2019). This work aims to classify troll memes by exploiting the visual and textual information. The task organizers[1] provided a dataset having two types of memes (troll and not troll) in Tamil (Suryawanshi and Chakravarthi, 2021).

Dataset	Train	Test
Troll	1282	395
Not-troll	1018	272
Total	2300	667

Table 1: Meme dataset distribution

Table 1 presents the distribution of the data samples in the train and test set. Dataset is provided in the form of an image with an associated caption. Participants can use the image, caption, or both to perform the classification task. We utilized image,

[1] https://competitions.codalab.org/competitions/36397

text, and multimodal (i.e., image + text) features to address the assigned task.

4 Methodology

The objective of this work is to identify the troll from multimodal memes. Initially, we exploit the visual aspects of the memes and develop several CNN architectures. Subsequently, the textual information is considered, and deep learning-based methods (i.e., LSTM, CNN, LSTM+CNN) are applied for classification. Finally, the visual and textual features are synergistically combined to make more robust meme classification inferences. Figure 2 depicts the abstract process of the troll meme classification system.

4.1 Data preprocessing

In the preprocessing step, unwanted symbols and punctuations are removed from the text automatically using a Python script. The preprocessed text is transformed into a vector of unique numbers. The Keras tokenizer function is utilized to find the mapping of this word to the index. The padding technique is applied to get equal length vectors. Similar to ImageNet's preprocessing method (Deng et al., 2009), all images are transformed into a size of $(224 \times 224 \times 3)$ during preprocessing.

4.2 Visual Approach

Several pre-trained CNN architectures including VGG16 (Simonyan and Zisserman, 2014), VGG19, and ResNet50 (He et al., 2016) are employed here. To accomplish the task, this work utilized the transfer learning approach (Tan et al., 2018). At first, the top two layers of the models are frozen and then added a global average pooling layer followed by a sigmoid layer for the classification. The models are trained using the 'binary_crossentropy' loss function and 'adam' optimizer with a learning rate of $1e^{-3}$. Training is performed by passing 32 samples at each iteration. Besides, we use the Keras callback method to save the best intermediate model.

4.3 Textual Approach

In order to extract features from the text modality, various deep learning architectures are used. The investigation employs CNN and RNN architectures, specifically CNN and LSTM with CNN (LSTM+CNN). Firstly, the Keras embedding layer generates the word embeddings for a maximum caption length of 1000. Subsequently, these embeddings are propagated to the models. We construct a CNN model consisting of one convolution layer associated with a filter size of 32 and a ReLU (Rectified Linear Unit) activation function in one architecture. To further downsample the convoluted features, we use a max-pooling layer followed by a classification layer for the prediction. In another architecture, we added a single LSTM layer of 100 neurons at the top of the CNN network and thus created the LSTM + CNN model. Here, the LSTM layer is introduced due to its effectiveness in capturing the long-term dependencies from the long text.

4.4 Multimodal Approach

Visual features are extracted using the pre-trained VGG16 model. Following the VGG16 model, we added a global average pooling layer with fully connected and sigmoid layers. We employed CNN and LSTM models to extract the textual features. Finally, the output layers of the visual and textual models are concatenated to form a single integrated model. The output prediction is produced in all combinations by a final sigmoid layer inserted after the multimodal concatenation layer. All the models are compiled with the 'binary crossentropy' loss function. Aside from that, we utilize the 'adam' optimizer with a learning rate of $1e^{-3}$ and a batch size of 32. Table 2 shows the list of tuned hyperparameters used in the experiment.

Hyperparameters	Values
Dropout rate	0.2
Epoch	15
Optimizer	'adam'
Learning rate	$1e^{-3}$
Batch size	32

Table 2: List of hyperparameters values.

5 Result and Analysis

The task's purpose is to categorize troll memes in Tamil. We experimented with various visual and textual models to deal with each modality. Furthermore, the features from both modalities were merged. The weighted f_1-score determines the models' superiority. Other evaluation criteria, such as precision and recall, are also considered to understand the model's performance better. Table 3 exhibits the evaluation results of the models on the test set. Concerning the multimodal approach, the

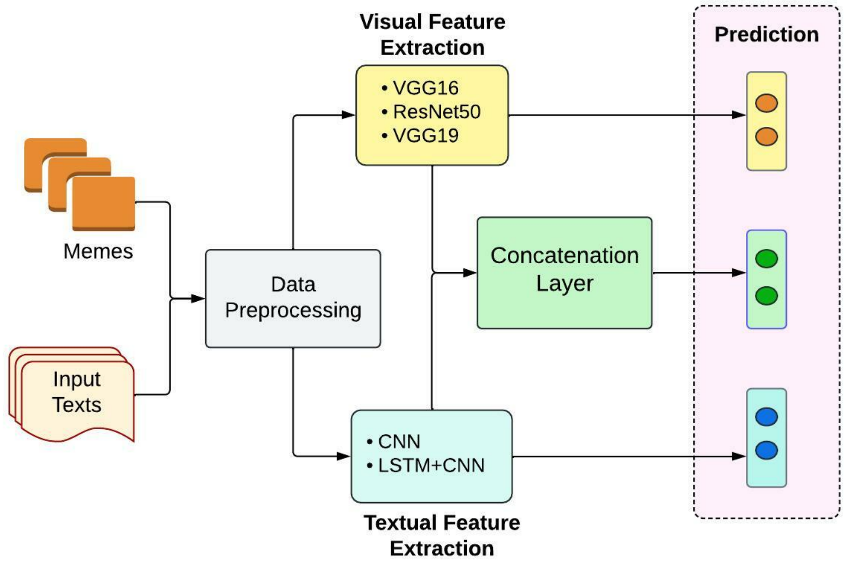


Figure 2: Abstract process of troll meme classification

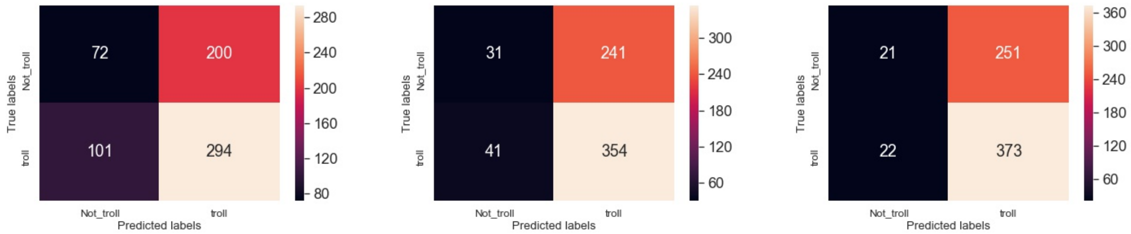
Approach	Classifier	Accuracy	Precision	Recall	f_1-score
Visual	VGG16	0.58	0.53	0.58	0.50
	ResNet50	0.58	0.50	0.58	0.45
	VGG19	0.55	0.51	0.55	0.50
Textual	CNN	0.55	0.52	0.55	0.52
	LSTM+CNN	0.55	0.54	0.57	0.52
Multimodal	LSTM+VGG16	0.58	0.44	0.58	0.44
	CNN-Text+VGG16	0.59	0.55	0.59	**0.49**
	CNN+LSTM+VGG16	0.59	0.49	0.58	0.46

Table 3: Evaluation results of visual, textual and multimodal models on the test set

CNN_Text+VGG16 model obtained a precision of 0.49 (not-troll class) and 0.60 (troll class) with a weighted average precision of 0.55. The overall performance of the models varies between 44% and 56% weighted f_1-score. The results indicate that VGG16 and VGG19 have the same weighted f_1-score, but VGG16 has superior precision and recall. Although ResNet50 has a lower f_1-score, its precision and recall are similar to VGG16. The performance of the text-based models proved superior to that of the image-based models. In the textual approach, CNN and LSTM + CNN both have the same f_1-score of 0.52.

We also conducted experiments by combining features from both modalities into a single model. In the multimodal approach, the LSTM + VGG16 model had a f_1-score of 0.44, whereas the CNN Text + VGG16 model had a 3% higher f_1-score of 0.49. However, their combination with 0.46 f_1-score could not outperform the textual-based models. According to the results, the multimodal model (CNN-Text +VGG16) outdoes others by acquiring the highest recall of 0.59 but could not perform well in terms of f_1-score. The presence of several images in all of the classes could cause this. The dataset contains many memes with the same visual content but distinct captions. Furthermore, many images do not convey any explicit useful information that can be utilized to determine whether a meme is a troll or not. Table 4 shows the performance comparison between the proposed (CUET89109115) and other models developed by shared task participating teams. With 0.529 f_1-score our team (CUET89109115) placed fourth in the competition. The implementation is available on the Github[2].

[2]https://github.com/Maruf089/DravidianLangTech-2022



(a) Textual (b) Visual (c) Multimodal

Figure 3: Confusion Matrix of the best model in each approach (based on f_1-score): (a) Textual (b) Visual (c) Multimodal

Team	Precision	Recall	f_1-score
BPHC	0.6	0.613	0.596
hate-alert	0.558	0.567	0.561
SSN_MLRG1	0.555	0.565	0.558
CUET89109115	0.527	0.531	0.529
DLRG_RR	0.529	0.529	0.519
TeamX	0.466	0.544	0.466

Table 4: Summary of performance comparison for all participating teams in the shared task

6 Error Analysis

A detailed error analysis is done on the best model for each modality to gain more insights. Confusion matrices are used to analyze the performance (Figure 3). Figure 3c shows that, out of 395 troll memes, the CNN Text + VGG16 model accurately categorized 373 images while misclassifying 22 as not-troll. However, this model's actual positive rate is lower than its true negative rate since it correctly classified just 21 not-troll memes and incorrectly classified 251 memes. The VGG16 model also performed well in the visual method, successfully detecting 354 troll memes out of 395. However, the model struggled to identify not-troll memes, correctly classifying only 31 of a total of 272 not-troll memes and incorrectly classifying 241 of the exact total. Meanwhile, Figure 3a shows that the CNN text model accurately categorized 294 of 395 troll memes, which is lower than the accuracy of other models. In comparison, the model accurately recognized only 72 non-troll memes out of 272. According to the results of the above investigation, all models are biased toward troll memes and incorrectly label more than 73% of memes as trolls. This improper detection is most likely due to the overlapping nature of memes across all classes. Furthermore, 80 memes in the train set and 34 memes in the test set were missed embedded captions, making it challenging for textual and multimodal models to predict the actual class.

7 Conclusion

This paper presented a deep learning model for detecting troll memes in Tamil. We experimented with visual, textual, and visual-textual fusion techniques. Results revealed that the visual approach obtained the highest weighted f_1-score of 0.50, whereas the textual approach (LSTM+CNN) achieved 0.52 f_1-score. However, after aggregating features from both modalities, we noticed a slight drop in the model performance. The combined CNN-Text+VGG16 model acquired the maximal weighted f_1-score (0.49) with multimodal approach outperformed other models. It will be interesting to catch how the multimodal fusion performs after extracting the visual and textual features with state-of-the-art models. We aim to investigate transformer-based models (e.g., vision transformer, IndicBERT, mBERT, XML-R, Electra, MuRIL) with the extended dataset in the future.

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