MUCS@LT-EDI-2024: Exploring Joint Representation for Memes Classification

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Abstract

Misogynistic memes are a category of memes which contain disrespectful language targeting women on social media platforms. Hence, detecting such memes is necessary in order to maintain a healthy social media environment. To address the challenges of detecting misogynistic memes, "Multitask Meme classification -Unraveling Misogynistic and Trolls in Online Memes: LT-EDI@EACL 2024" shared task organized at European Chapter of the Association for Computational Linguistics (EACL) 2024, invites researchers to develop models to detect misogynistic memes in Tamil and Malayalam. The shared task has two subtasks and in this paper, we - team MUCS, describe the learning models submitted to Task 1 - Identification of Misogynistic Memes in Tamil and Malayalam. As memes represent multi-modal data of image and text, three models: i) Bidirectional Encoder Representations from Transformers (BERT)+Residual Network (ResNet)-50, ii) Multilingual Representations for Indian Languages (MuRIL)+ResNet-50, and iii) multilingual BERT (mBERT)+ResNet-50, are proposed based on joint representation of text and image, for detecting misogynistic memes in Tamil and Malayalam. Among the proposed models, mBERT+ResNet-50 and MuRIL+ ResNet-50 models obtained macro F1 scores of 0.73 and 0.87 for Tamil and Malavalam datasets respectively securing 1st rank for both the datasets in the shared task.

1 Introduction

Memes, in the digital age, have become a common form of cultural expression, often shared widely across social media platforms and internet communities. These memes typically comprising of images/videos and text embedded on them, started with the idea of sharing humor (Suryawanshi et al., 2020). But these days, memes are often being misused to spread hateful, troll, and misogynistic content. Misogynistic memes are a category of memes that propagate negative attitude towards women. These memes often promote dangerous or harmful pranks, challenges, or behaviors which leads to physical harm, injury, or legal consequences (Guest et al., 2021; Hegde et al., 2021). Hence, it is necessary to detect such content to protect users from getting harmed and also to maintain a safe and inclusive online environment.

Detecting misogynistic memes on social media is challenging due to the combination of text, image/video, and sometimes audio also, which exhibits a multi-modal nature. This problem becomes more challenging when the embedded text belongs to low-resource languages like Tamil, Malayalam etc., where lack of digital resources and computational tools is the common issue. "Multitask Meme Classification - Unraveling Misogynistic and Trolls in Online Memes: LT-EDI@EACL 2024" (Chakravarthi et al., 2024) shared task encourages the researchers to develop models to detect misogynistic and trolling content in Tamil and Malayalam memes. The shared task has two subtasks and in this paper, we - team MUCS, describe the learning models submitted to Task 1 - Identification of Misogynistic Memes in Tamil and Malayalam. As memes are made up of textual and visual components, they can be represented as multimodal data of textual and visual features integrated into a single representation known as joint representation. Three models: i) BERT+ResNet-50, ii) MuRIL+ResNet-50, and iii) mBERT+ResNet-50, are proposed based on joint representation, for detecting misogynistic memes in Tamil and Malayalam.

The rest of the paper is arranged as follows: a review of related work is included in Section 2 and the methodology is discussed in Section 3. Experiments and results are described in Section 4 followed by concluding the paper with future work in Section 5.

2 Related work

Researchers have explored several models for detecting memes by representing the visual and textual components of memes as two uni-modal data as well as integrating visual and textual components into a single joint representation. Few of such relevant research works are described below: Raha et al. (2022) have explored uni-modal (Image-Grid, Image-Region, Text BERT, Text Robustly Optimized BERT Pre-training Approach (RoBERTa), Uni-modal fusions (Concat-BERT, Late Fusion), Multi-modal transformers (Multi-Modal BiTransformer (MMBT)-Grid, MMBT-Region, Visionand-Language BERT (ViLBERT), Visual BERT) and pre-trained models (ViLBERT CC, Visual BERT COCO, VILBERT HM, Visual BERT HM), for identifying misogynous memes in Conceptual Captions (CC), Common Objects in Context (COCO), Hateful Memes (HM) datasets. Among all the proposed models, the VilBERT HM model outperformed all other models obtaining macro F1 score of 0.712 for HM dataset. Muti et al. (2022) proposed uni-modal and multi-modal approaches for identifying misogynistic memes in English dataset. The multi-modal system is implemented by fusing image and text embeddings through MMBT which is used to jointly fine-tune uni-modal pre-trained text and image encoders by projecting image embeddings to the text token space. Their proposed multi-modal system obtained a macro average F1 score of 0.727.

Maheshwari and Nangi (2022) experimented various Machine Learning (ML), Deep Learning (DL) and Transfer Learning (TL) based models for the identification of misogynous memes in English. Their ML models (Support Vector Machine (SVM), Naive Bayes (NB) and Logistic Regression (LR)) are trained with Term Frequency-Inverse Document Frequency (TF-IDF) of word unigrams (text representation) and pre-trained Visual Geometry Group-16 (VGG-16) (image representation), DL models (LSTM and Convolutional Neural Network (CNN)) are trained with GloVe embeddings (text representation) and VGG-16 (image representation) and TL models are trained with BERT variants (Concat BERT, Average BERT, and Gated BERT) (text representation) and Common World Knowledge (CWK) and Contrastive Language-Image Pretraining (CLIP) (image representation). The authors experimented all the models with uni-modal feature space, i.e, training the classifiers with only

text and only image features and also with joint learning i.e., training the classifiers with shared embedding layer for both text and image features. Among all their models, TL model with joint learning using Average BERT + CLIP achieved a macro F1 score of 0.671.

Sean and Kanchana (2022) presented multimodal models, namely InceptionV3+BERT backbone as Model A, EfficientNetB7+BERT as Model B, CLIP Image+CLIP Text Backbone as Model C, SVM and an Ensemble model (Model A, Model B, SVM), for identifying misogynous memes in English. Among the proposed models, Ensemble model achieved a macro F1 score of 0.718. Rao and Rao (2022) experimented text-based (Bidirectional Long Short Term Memory (BiLSTM)+Glove embeddings, RoBERTa, Ernie-2.0), image-based (VGG-16, ResNet-50, ResNet-152, Vision Transformer), and multi-modal (VGG-16+BiLSTM, MMBT, VisualBERT, MMBT with tRoBERTa, and Average (Avg) Ensemble (RoBERTa and ResNet-152 models with soft voting)) models, for misogynous meme identification in English language. Among their proposed models, the Avg Ensemble model outperformed other models with a macro F1 score of 0.761. Gu et al. (2022) employed an ensemble of ML models (Multinomial NB (MNB) and Gradient Boosting classifiers trained with TF-IDF of word bigrams and unigrams respectively, and Random forest (RF) classifier trained with various image features (Hu moment invariants, Haralick textures, and image histograms), for the identification of misogynous memes. In addition, the ML models of the ensemble are also trained independently with the respective features as mentioned. Among all their models, RF classifier trained with various image features outperformed other models by achieving a macro F1 score of 0.665.

The above literature reveals that the joint representation of image and text exhibits promising performances for meme detection tasks. However, most of the meme detection tasks focus on English language giving less importance for low-resource languages like Tamil and Malayalam.

3 Methodology

The objective of this work is to identify misogynistic memes in the given Tamil and Malayalam datasets. This is achieved by proposing learning models based on the joint representation of image and text components in the given memes. The steps

| Language | Image | Text | English Translation | Label |
|-----------|--|--|---|-----------------|
| Malayalam | ee add en same yn gaalad nas eryn gaalges plaa amad eryn gaal diwr edan o eryn gaal diwr edan o eraan Martin yn gallan Martin yn gallan Martin gallan Martin gallan Martin gallan | ഭാര്യ ആയിട്ട് ഒന്നും നടക്കുന്നില്ല എന്ന് ഇടക്കിടക്ക് സങ്കടം പറയുന്ന മുതലാളിയുടെ റൂമിലേക്ക് കടന്നപ്പോൾ ഭാര്യയെ ഒറ്റക്കാലിൽ നിർത്തി കളിക്കുന്നത് കണ്ട വേലക്കാരി* നിർത്തിയങ്ങു അടിക്കുവായിരുന്നല്ലേ | When she entered the boss's room, who often complained that nothing was going on as a wife, the maid stopped and saw her playing on one leg. | Misogyny |
| | | ഐഡിയ 4G ഹന്ഥിൽ - മലയാളം വീടിന്റെ മുറ്റത്ത് 2G വിടിന്റെ ഹാളിൽ എന്റെ റൂമിൽ | Idea 4G Humpil - Malayalam In the yard of the house 2G in the hall of the house in my room | Not Misogyny |
| Tamil | -итвит якника Орбция? - царацаяк: Орбцатал. "Абди и драня «Орабтати аписья» Сави искос. Соли-, "Абди апотици и кака докого | ~மாமியார் சமைக்க தெரியுமா? புதுமருமகள் தெரியுமாவா அடுப்ப பத்தவச்சு சுடுதண்ணிய காயவச்சு மேகி பக்கெட்ட கொட்டி அப்டியே கரண்டிய வச்சு அலசுவம் | ~ Does mother-in-law know how to cook? Do you know, newlyweds that the stove is heated, the water is heated, the water is dry, the bucket is poured, and the spoon is cleaned? | Misogyny |
| | | mட எரிச்சாலும் திரும்ப திரும்ப எழுந்து வர phoenix bird எங்க SILUKKU DOT COM முட்டை போட்டதுக்கே குண்டி வலிக்குதுனுபுலம்புற நீ எங்க | Get up again and again with irritation phoenix bird where sila silukku dot com Where are you after laying the eggs and the pain in the stomach? | Not Misogyny |

Table 1: Sample Malayalam and Tamil memes (image and text data) with corresponding labels

| Tamil | | | | | |
|--------------|-----------|---------|--|--|--|
| Label | Train set | Dev set | | | |
| Misogyny | 274 | 76 | | | |
| Not Misogyny | 863 | 209 | | | |
| Malayalam | | | | | |
| Misogyny | 256 | 64 | | | |
| Not Misogyny | 384 | 96 | | | |

Table 2: Class-wise distribution of memes in Tamil andMalayalam datasets

involved in the methodology are explained below:

3.1 Pre-processing

Pre-processing is a crucial step that cleans the data and prepares it for further processing. Usually, images will be of varying sizes as they will be collected from different sources and hence they are resized to a standard size. Further, images not in RGB format are converted to RGB format. Punctuation, digits, urls, and hashtags are considered as noise and hence are removed from the textual component. English stopwords (memes may also include English words), available at NLTK¹ library and Tamil stopwords from a GitHub² repository are utilized as references for removing English and Tamil stopwords from Tamil dataset respec-

e82a5a331f78a5cc9b6d372df13a919c

tively and only English stopwords are removed from Malayalam datasets.

3.2 Construction of Learning Models

In DL, feature extraction and classifier construction go hand-in-hand. As memes contain image and embedded text, a joint representation of integrating image and text features is used in this work. The image and text encoders used to represent image and text respectively are described below:

• Text Representation - Transformer models have emerged as promising pre-trained models for extracting features from text due to their ability to capture intricate contextual relationships between words in the given input sequence. Their self-attention mechanisms enable a comprehensive understanding of word dependencies, allowing for the creation of context-rich embeddings that enhance the performance of many downstream natural language processing tasks. In this work, BERT³ (Devlin et al., 2018), MuRIL⁴ (Khanuja et al., 2021), and mBERT⁵ (Devlin et al., 2018), are used to represent text as three different models. BERT is pre-trained on a large amount of English text in a self-supervised fashion

¹https://pythonspot.com/nltk-stop-words

²https://gist.github.com/arulrajnet/

³https://huggingface.co/bert-base-uncased

⁴https://huggingface.co/google/muril-base-cased

⁵https://huggingface.co/bert-base-multilingual-cased

| Language | Tamil | | | | | |
|-----------------|-----------|--------|----------|-----------|--------|----------|
| Model | Dev set | | Test set | | | |
| Widder | Precision | Recall | F1 score | Precision | Recall | F1 score |
| BERT+ResNet-50 | 0.72 | 0.70 | 0.71 | 0.68 | 0.65 | 0.66 |
| MuRIL+ResNet-50 | 0.77 | 0.72 | 0.74 | 0.75 | 0.64 | 0.66 |
| mBERT+ResNet-50 | 0.75 | 0.72 | 0.73 | 0.77 | 0.72 | 0.73 |
| Language | Malayalam | | | | | |
| BERT+ResNet-50 | 0.82 | 0.80 | 0.81 | 0.82 | 0.83 | 0.82 |
| MuRIL+ResNet-50 | 0.86 | 0.80 | 0.81 | 0.90 | 0.87 | 0.87 |
| mBERT+ResNet-50 | 0.77 | 0.75 | 0.76 | 0.85 | 0.84 | 0.84 |

Table 3: Performances of the proposed models for identifying misogynistic memes in Tamil and Malayalam datasets

using a Masked Language Modeling (MLM) objective whereas MuRIL and mBERT are multilingual pre-trained models which support Tamil and Malayalam languages. While MuRIL supports 17 Indian languages in their native and transliterated scripts, mBERT supports 104 languages in their native script. BERT is used as the given Tamil and Malayalam datasets contain English texts along with Tamil and Malayalam text in their native script.

• Image Representation - ResNet-50⁶ (He et al., 2016) - a CNN with 48 Convolution layers along with 1 Max Pool and 1 Average Pool layer and a fully connected layer, is a variant of ResNet which is pre-trained on ImageNet (Deng et al., 2009) dataset at a resolution of 224x224. ReseNet-50 is used as image encoder to obtain the image features.

Dual-encoder architecture which is based on joint representation approach is used to concatenate image and text encoders and the joint encodings are passed through linear layers to build the classifier model for identifying misogynistic memes in Tamil and Malayalam.



Figure 1: Comparison of macro F1 scores of the participating teams in the shared task

-96

4 Experiments and Results

Tamil and Malayalam memes datasets provided by the organizers of the shared task are labeled as 'Misogyny' and 'Not Misogyny' memes, for the task of binary classification (Chakravarthi et al., 2024). The sample memes with their corresponding labels and class-wise distribution of Tamil and Malayalam memes datasets are shown in Tables 1 and 2 respectively. Table 3 shows the performances of the proposed models. Among the proposed models, mBERT+ResNet-50 and MuRIL+ResNet-50 models obtained better macro F1 scores of 0.73 and 0.87 for Tamil and Malayalam datasets respectively, securing 1st rank for both the datasets in the shared task. Figure 1 gives a comparison of macro F1 scores of all the participating teams in the shared task.

4.1 Error Analysis

Few misclassified memes along with the actual and predicted labels obtained from mBERT+ResNet-50 and MuRIL+ResNet-50 for Tamil and Malayalam datasets respectively, are shown in Table 4. Misclassifications are due to the limitations of image and text encoders. Text encoders may fail to capture the domain specific meaning of the ambiguous words. Further, there are a few content words or phrases that are often used in the context of one polarity; however, the ground truth of the Test data with same words or phrases has a different polarity. For example, during training, the words or phrases 'quick', 'show', and 'in front of' are often used in the context of 'Misogyny' and the ground truth of this transcription is 'Not Misogyny'. From the image point of view, features that affect the identification of misogynistic memes include noise in the image, image quality, size of the training image dataset, and architecture of the image encoder.

⁶https://iq.opengenus.org/resnet50-architecture/

| Language | | amil | Malayalam | | |
|------------------------|--|--|--|--|--|
| Meme | Sunh Hán Arme dươ Qạg ednar. 8 ອູງາມ seara - ເງິດແຜ່ ຄ ກ່າວນີ້ ອີງແມ່ນ ແຂ້ກັງເລ້ອງ ອາສັດອູ ລິງກີນປຸ່ວ. | An online costs of the set of the | | പെടുന്ന് വേഷ്യപെടുന്നവർ, എത്ര വലിയ കലിപ് കാണിച്ചാലും ന്നെ കലിപ് അൻ ഇഷ്യകാടുന്നവരുടെ എന്നിൽ ഖത്രഖയിക്കെം കാണിക്കാല്ല! | |
| Transcription | South Indian Aunties during சண்டை & குழாயடி சண்டை நீஎவன் கூட எல்லாம் தொடர்பு வச்சிருக்கனு எனக்கு தெரியும்டி தெரு | அவ என்னை ஏமாத்துனத கூட மன்னிச்சிடுவேன் டா ஆனா? அவ புள்ளய விட்டு என்னை மாமாயன்னு கூப்பிட வச்சா பாரு ~ மறக்கவே முடியல dude | ബ്ലൗസും പാവാടയുമുടുത്തു ള്ള സിൻ കാണുമ്പോൾ | പെട്ടെന്ന് ദേഷ്യപെടുന്നവർ, എത്ര വലിയ കലിപ്പ് കാണിച്ചാലും ആ കലിപ്പ് അവർ ഇഷ്ടപ്പെടുന്നവരുടെ മുന്നിൽ മാത്രമായിരിക്കും കാണിക്കുള്ളു! | |
| English Translation | South Indian Aunties during fight & Pipe fight I know that even you are connected to the street | Even if she cheated on me, I will forgive her. She left the room and called me Mamayan ~ never forget dude | Seeing Sin in a blouse and skirt | People who are quick to anger, no matter how much anger they show, that anger is only shown in front of those they love! | |
| Actual Label | Misogyny | Not Misogyny | Misogyny | Not Misogyny | |
| Predicted Label | Not Misogyny | Misogyny | Not Misogyny | Misogyny | |

Table 4: Few misclassified Tamil and Malayalam memes with actual and predicted labels

Added to this is the imbalance nature of the given datasets where both Tamil and Malayalam datasets contain less number of 'Misogyny' memes.

5 Conclusion and Future Work

This paper describes, three models: i) BERT+ResNet-50, ii) MuRIL+ResNet-50, and iii) mBERT+ResNet-50, based on joint representation of text and image features, for detecting misogynistic memes in Tamil and Malayalam datasets, submitted by our team - MUCS to "Multitask Meme classification -Unraveling Misogynistic and Trolls in Online LT-EDI@EACL 2024" shared task. Memes: Among the proposed models, mBERT+ResNet-50 and MuRIL+ResNet-50 models obtained macro F1 scores of 0.73 and 0.87 for Tamil and Malayalam datasets respectively, securing 1st rank for both the datasets in the shared task. More efficient joint representations that improve the performance of the learning models will be explored further.

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