**Abstract**—Text Classification is an integral part of many Natural Language Processing tasks such as sarcasm detection, sentiment analysis and many more such applications. Many e-commerce websites, social-media/entertainment platforms use such models to enhance user-experience to generate traffic and thus revenue on their platforms. In this paper, we are presenting our solution to Multilingual Abusive Comment Identification Challenge on Moj, an Indian video-sharing social networking service, powered by ShareChat and IIIT-Delhi for the 2nd Workshop on Emerging Advances in Multimodal AI (EAM) at IEEE BigMM, 2021. The challenge dealt with detecting abusive comments, in 13 regional Indic languages, on the videos on Moj platform. Our solution utilizes the novel $\mu$Boost, an ensemble of CatBoost classifier models and Multilingual Representations for Indian Languages (MURIL) model, to produce SOTA performance on Indic text classification tasks. We were able to achieve a mean F1-score of 89.286 on the test data, an improvement over baseline MURIL model with a F1-score of 87.48.

I. INTRODUCTION

With internet becoming more and more accessible to users there is an exponential growth in number of websites and platforms across all the sectors and markets. On one hand we have some juggernauts in e-commerce space selling useful products to customers and on the other hand we have social media/entertainment platforms influencing the way people live and even behave. While there’s a lot of work going on to increase the engagement of users on these platforms and thus directly affecting the revenue growth, there’s relatively less work going on to regulate the content shared on such platforms. In recent times, people and organizations have become more cognizant of shared responsibility of tackling racial/ethnic discrimination and detecting offensive and abusive language written on online platforms. This competition, hosted on Kaggle, was structured around the same thought. The goal of the challenge was to find abusive comments using natural language processing on popular Indian short-video sharing app Moj, owned by parent company ShareChat. The training data was gold standard human annotated. The unique thing about the data provided was that the comments were multilingual in 13 different regional Indic languages such as Kannada, Tamil, Telugu, Hindi, Gujarati, Bhojpuri, Marathi, Malayalam, Bengali, Odia, Haryanvi, Rajasthani, and Assamese. Apart from this, there were 5 other independent features such as number of likes, number of reports etc., that provided meta-data about the comments.

II. DATA

The dataset consisted of the following columns:

- language : Language of the post on which this comment was made.
- post_index : Unique post identifier having this comment.
- commentText : Comment as a string
- report_count_comment : Number of times comment has been reported.
- report_count_post : Total number of reports on all comments of this post.
- like_count_comment : Number of likes on the comment
- like_count_post : Total number of likes on all comments of this post
- label : 0-Non-abusive; 1-abusive

A. Exploratory Data Analysis

The training dataset had 665042 rows and 7 independent features (X) and 1 binary target feature ‘label’ indicating whether the comment is abusive or not. 52.98% of comments were labeled as non-abusive and 47.02% of comments were labeled as abusive indicating a balanced class dataset. The average number of words in the comments, tokenized on space, were 12.7. Around 46% of the comments were in Hindi/Hinglish, 14.5% in Telugu, 10.8% in Marathi, 6.1% in Malayalam, 3.4% in Bengali, 2% in Kannada, 1.6% in Odia, 1.3% in Gujarati, 1.3% in Haryanvi, 0.8% in Bhojpuri, 0.6% in Rajasthani and 0.4% in Assamese. There were 391117 unique post indexes. The distribution of other features are presented in table I.

III. EMBEDDING BASED APPROACHES

We tried multiple approaches before coming up with $\mu$-boost. In this section we will briefly describe various approaches that we have taken and their results.

We have split the data as 99% train and 1% dev set. This split is used across all experiments.

A. BiLSTM and BiGRU

Recurrent neural network models have been known to perform very well on NLP tasks[1]. Based on this understanding we built our baseline model using 2 layers of BiLSTM[1], [2]. The first BiLSTM layer was provided with embeddings learnt by Keras’ Embedding layer having a dimension of 64x120. For this experiment we relied on Keras’ inbuilt tokenizer. One thing to note here is that we only resorted to the text
column in the input data. We did not use any other column from the provided dataset. The number of LSTM nodes used were 64, and 32 in first and second layers respectively. The baseline F1 score obtained by this model on the training set was 87.515 and on the test set was 86.432. This model also showed signs of overfitting in very early stages of training. We also experimented with replacing LSTM units with GRU units in the BiLSTM layer. The F1 score of BiGRU model on the training set was 88.511 and on the test set was 86.560. We calculated these F1 scores at the probability threshold of 0.5. Both these models were trained on Google Colab’s 12 GB GPU-RAM instance and took approximately 1 hour to train. The next logical step was to use pretrained models or word embeddings.

### B. MuRIL

MuRIL stands for Multilingual Representations for Indian Languages. This approach is currently the SOTA for Indian Language models. It out-performs mBert on Indian Language models. MuRIL uses transformers [3] as building blocks of the model. Transformers incorporate self-attention in the encoder layers, and both self-attention and encoder attention in the decoder layers. This gives transformers an edge over recurrent models like LSTMs which receive input one word/step at a time and have difficulty in learning very long term dependencies which occur in natural language.

The differentiating factor of this model with respect to BERT is that it is trained only on data of Indic Languages, and is trained on both translated and transliterated datasets.

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**TABLE 1**

| Column Name          | Mean   | Standard deviation | Maximum |
|----------------------|--------|--------------------|---------|
| report_count_comment | 0.0052 | 0.08               | 8       |
| report_count_post    | 0.2171 | 13.64              | 3359    |
| like_count_comment   | 0.6865 | 7                  | 2344    |
| like_count_post      | 255.952| 2548.12            | 104159  |

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We relied on MuRIL’s tokenizer for processing raw text. This model was trained for 12 epochs with max_len of 64 and batch size of 128. We also used a dropout layer on the output of transformer layer with dropout ratio of 0.2 to regularize the model. The optimizer used was ADAM with a learning rate of 1e-5.

Our approach to using MuRIL is inspired by the Kaggle notebook [4] that had a test F1 score of 87.48 with a corresponding training F1 score of 88.353 at probability threshold of 0.5. It took us approximately 4.5 hours to train this model on default kaggle TPU instance.

### IV. BAG-OF-WORDS BASED APPROACHES

In order to improve the above MURIL model in a world where powerful deep learning algorithms are ruling the arena, we chose to train a simple Bag of Words model [5].

#### A. Choice of classifier

As discussed in previous sections, predicting a comment as abusive or non-abusive is a typical text classification task. In order to build this model, we had to decide which classifier to choose. We chose CatBoost as our classifier, which is based on the principles of Gradient-Boosted tree framework, to predict the probabilities of a comment being abusive. The dataset was structured in nature with categorical columns such as post_index with a very high cardinality.

The most common approach to handle categorical columns is to do one-hot encoding [6], [7], [8] but that would have led to creation of high dimensional feature vectors which can worsen model performance and increase training time. Other methods such as target encoding [8] are also sensitive to target leakage. Classifiers such as XGBoost has shown great performance on variety of structured datasets, but they consume more memory as compared to CatBoost[9].

CatBoost models can also be trained very easily on GPUs by passing an argument task_type as GPU. Another reason for choosing CatBoost as the classifier was its ability to handle categorical variables without the risk of target leakage[10]. CatBoost performs Ordered Target encoding to encode categorical variables. To encode a particular category via ordered target encoding CatBoost utilizes label information of the respective categories’ instances that occurred prior to current instance. For example, in the table language feature category Hindi, where i denotes the i-th instance of that category, will

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**Fig. 1. MuRIL Training and Dev Loss**

MuRIL covers 17 languages, however, some of the languages required by the competition are not covered by MuRIL for which we will discuss our solution in the next section. A pretrained model for MuRIL is generously made available by the MuRIL authors on huggingface, which we have used in this experiment.

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TABLE II
COMPARISON OF VARIOUS MODELS

|        | BiLSTM | BiGRU | Single CatBoost | Ensemble CatBoost | MuRIL | $\mu$Boost |
|--------|--------|-------|-----------------|-------------------|-------|------------|
| Train F1 | 87.515 | 88.511 | 92.171          | 92.961            | 88.35 | 92.831     |
| Test F1  | 86.432 | 86.560 | 87.153          | 87.409            | 87.48 | 89.282     |

TABLE III
ORDERED TARGET ENCODING

| language | label |
|----------|-------|
| Hindi    | 1     |
| Hindi    | 0     |
| Marathi  | 0     |
| Hindi    | 1     |

get encoded by the formula 1. It also assigns a prior value to avoid undefined values in encoding.

$$Hindi_i \rightarrow \frac{1 + 0 + a \times Prior}{2 + a}$$  \hspace{1cm} (1)

where $a$ is a constant

B. Text features in CatBoost

Apart from handling categorical features, CatBoost can also handle text features internally quite well via the `text_features` class. It provides variety of text preprocessing steps on the fly. It can tokenize and lowercase the text by splitting each sentence into words or letters. Then it creates a dictionary that collects all values of text feature and numbers the minimum unit of text sequence representation called a token. Apart from this it also provides control of n-gram tokenization as combining tokens can be useful to perceive contiguous text. It is also possible to filter rare occurring words and specify the maximum dictionary size[11]. The text features are represented as numerical features by Bag of Words (BoW) representation where a Boolean flag reflects whether the text contains the token or not. This has the problem of sparse representation as compared to other embedding vector representations that are generally used in deep learning models, but it can be controlled and tuned by varying the `max_dictionary_size` and `top_tokens_count` hyperparameters.

These computed sparse numerical features are then fed into regular CatBoost training algorithm. To begin with, we trained a simple CatBoost classifier on Google Colab’s 12 GB RAM Nvidia GPU. We kept 99% of the data in train set and rest 1% in development set. Categorical features that were fed into CatBoost were the columns `language` and `post_index`. The feature `commentText` was passed as the text feature. The `max_dictionary_size` was set to 800000 and `top_tokens_count` to only 16000. We trained the model for 15000 iterations with F1 score as the evaluation metric. CatBoost also incorporates an overfitting detector, `od_wait`, and can stop training if score doesn’t improve for specified number of iterations. We kept the `od_wait` hyperparameter as 2000 iterations. The `learning_rate` was set to 0.35 and `depth` as 12. The model gave train F1 score of 92.171 and test F1 score of 87.154 at 0.5 probability threshold.

C. Ensembling CatBoost Models

Continuing our experiments, we next explored the effect of ensembling of CatBoost models on the performance metrics. Here, we trained 3 CatBoost models in a loop with different seed parameters but same configurations in order to predict the probabilities of abusive comments. The time taken to train this ensemble model with overfitting detector was approximately 1.45 hours. The probabilities were then averaged across the three trained models to get final prediction probabilities. The train F1 score increased to 92.961 and test F1 score to 87.409, with a probability threshold of 0.5.

V. $\mu$Boost

In this section we propose a novel effective method to solve text classification for Indic languages: $\mu$Boost. The learnings for its effectiveness are based on our experiments that we performed in this competition.
As next step to improve the performance of the model, we tried ensembling the predictions of MURIL and ensemble CatBoost - μBoost. The motivation behind doing this came from the fact that there were some languages such as Bhojpuri, Haryanvi and Rajasthani that were present in the dataset and for which language models like MURIL doesn’t have adequate representation. Predictions for such languages can be improved from the trained BoW ensemble CatBoost models. Also, ensembling methods can sometimes boost the model performance [12] for variety of classification tasks. Here we averaged the individual predicted probabilities from each of the 3 trained CatBoost models with that of MURIL model to get the final abuse comment prediction probability. With a probability threshold of 0.5, the train F1 score shot up to 92.831 and test F1 score to 89.282, which was a considerable improvement in test-set performance.

VI. THRESHOLD TUNING

The class distribution of abusive to non-abusive comments in dataset was 1:1.12, which puts it in nearly balanced-class category dataset where there is almost equal representation from both the classes of labels. We tried tuning the probability threshold to improve the model’s F1 score by varying it over the range [0.45,0.55]. The choice of range was based on the fact that the dataset was nearly balanced in nature. We observed the maximum F1-score at 0.49 probability threshold that gave an F1-score of 89.286.

VII. FUTURE WORK

The μBoost method significantly improved the model’s performance on unseen data. However, there are many more ways by which it can be improved even further. Since μBoost is made up CatBoost models and MURIL, each of the two can be improved individually to improve the overall performance of the ensemble. Some of the ways could be as follows:

- Tuning plethora of hyperparameters such as depth, learning_rate, 12_leaf_reg etc. of CatBoost model and epoch, max_len etc. of MURIL model via some hyperparameter search method.
- Increasing the ensemble size of CatBoost models.
- Using a model-based approach, apart from averaging out, to combine the individual probabilities of the models in the ensemble to improve the performance.
- Explore other models in the ensemble which can ameliorate the overall model performance.

VIII. CONCLUSION

Table II shows the performance of all our experiments on train and test datasets. As the result of these set of experiments, we would like to draw the following conclusions:

- CatBoost model applied on bag of words performs almost at-par with MuRIL. Therefore, we show that CatBoost suitable for NLP tasks.
- Ensemble of models, Catboost in this instance, outperform single model based approaches.
- μBoost outperforms all other component models. Our hypothesis is that μBoost picks up the slack in inputs of languages that are not handled by MuRIL.

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