Fake News Detection in Telugu Language using Transformers Models

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***Abstract*—In today's world, lots of people rely on online news every day. But with more people using websites for information, there's a growing problem of wrong info spreading. This can make it hard to trust news, especially on social media. Detecting fake news online has become really important because it can cause problems for individuals and groups. While there's been a lot of work done on detecting fake news in popular languages, not much attention has been given to languages with fewer resources. We created a new dataset to address this issue in the detection of fake news in the Telugu language. We used different transformer models like mBERT, XLM-RoBERTa, IndicBERT, and MuRIL for fine-tuning the models in detecting fake news. MuRIL outperformed the rest of these models, obtaining an accuracy of 88.79%. MuRIL demonstrated the highest accuracy in classifying more number misleading news correctly.**

***Index Terms*—Fake News, high-resource, low-resource, Transformers**

I. Introduction

Fake news has become a major problem in the digital age for online information transmission because of its widespread distribution. With the speed at which false information circulates across several platforms, it has become harder and harder to verify the legitimacy of news reports, particularly in low-resource language. Dravidian languages, which do not have enough parallel data, are said to have insufficient resources, which includes Telugu. The lack of lengthy written texts exacerbates this resource shortage even more. Due to the limited availability of linguistic resources, there isn't much research done on these languages. There is still a noticeable gap in our understanding of the subtleties of disinformation in low-resource languages, especially those in the Dravidian language family, despite the advances achieved in the past in identifying false information in popular languages. Previous studies, including that of Eduri et al., have established preliminary frameworks for the identification of fake news in Dravidian language contexts. But more sophisticated methods that take into consideration the complex nature of disinformation are still required, especially for languages like Telugu. In order to address this gap, our paper introduces a novel contribution focused specifically on the detection of fake news in the Telugu language.

The main contribution in this study is the compilation of an extensive dataset designed especially for Telugu false news identification from our SCalAR [1] research group. Understanding the difficulties associated with data scarcity and linguistic variation in low-resource languages, we extensively collected a wide range of articles from reliable sources, including genuine, misleading, and fake news, to create a solid dataset representative of actual situations.to construct a robust dataset reflective of real-world scenarios. Our study employs a multilabel classification framework that includes three different categories: Fake, Misleading, and Not-Fake, in contrast to standard binary classification techniques that only identify between fake and actual news. We want to improve the effectiveness and accuracy of our detection algorithms by capturing the many forms of misinformation that are common in online conversation by implementing this sophisticated approach. Our work utilizes advanced transformer models, including mBERT, XLM-RoBERTa, IndicBERT, and MuRIL, and applies fine-tuning techniques to customize these models for Telugu fake news identification. By means of careful evaluation and model optimization, our aim is to clarify the complex linguistic complexities present in Dravidian languages, thereby contributing to the domain of false news identification in linguistically diverse contexts ahead. We present promising performance measures for all models based on our experimental findings, with a focus on accurately identifying false news articles. We want to give real-world insight into the opportunities and challenges related to fake news identification in Telugu by carefully testing the performance of our models.

In summary, our paper represents a significant step forward in the ongoing efforts to combat misinformation in linguistically diverse environments. By introducing a novel dataset, adopting a multilabel classification approach, and leveraging advanced transformer models, we endeavor to empower researchers and practitioners with the tools and methodologies necessary to address the complex realities of fake news detection in Telugu and beyond.

II. Related Work

Four transformer models were used in the study to analyse Kannada, Telugu, Tamil, and Malayalam: mBERT, XLM-RoBERTa, IndicBERT, and MuRIL. When compared to the other models, MuRIL showed the highest accuracy [1].

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[1] https://scalar-nitk.github.io/website/#home

A unique dataset called Dravidian-Fake is presented for the purpose of detecting fake news in the framework of four Dravidian languages: Tamil,Telugu,Malayalam, and Kannada. This is the first dataset created with the specific goal of identifying fake news in Dravidian languages. The collection, which includes about 26,000 news stories in these languages, is a useful tool. Using a novel approach to adaptive learning, the researchers improved the trained transformer model's performance. Adaptive learning was used to fine-tune the multilingual trained transformer model on a composite dataset consisting of false news reports in Dravidian and English. The study aimed to evaluate how well these refined models identified fake news in the Dravidian fake news dataset by applying methods based on transfer learning [2].

This study uses Google's MuRIL model to address the problem of identifying fake news in Dravidian languages. It investigates the possibilities of transformer-based models for understanding context and linguistic analysis. Using a labeled dataset, researchers improve the "MuRIL-base-cased" revision by supervised learning. The refined model analyses fresh content during the inference stage to distinguish between real and illegal news. MuRIL outperforms state-of-the-art models with an accuracy of 93.97% on the Dravidian-Fake dataset, according to evaluation using traditional metrics. This demonstrates MuRIL's robustness in detecting fake news in multiple languages [3].

A mixed deep learning approach is presented by researchers to identify fake news in Dravidian languages that have limited resources. The model combines a contextualized attention mechanism (CAM), bidirectional long-short-term memory (BiLSTM), and dilated temporal convolutional neural networks (DTCN). BiLSTM effectively captures long-range dependencies, DTCN captures temporal dependencies, and CAM highlights important information while minimizing irrelevant stuff. Adaptive-based cycle learning rates and an early prevention mechanism are included to help with convergence. This combination improves the model's ability to detect fake news in Dravidian languages with limited resources [4].

Using transfer learning principles, the researchers have created a Multi-Linguistic Fake News Detection model. This method is used since, in contrast with English, it is more difficult to obtain significant data sets for local or Indian languages. Google's bert-base-multilingual-uncased version of BERT is used to train the model. The study's dataset was obtained from trusted fact-checking websites, specifically PolitiFact and BuzzFeed. Reliable datasets and a clever combination of transfer learning and a multilingual BERT model improve the machine's ability to identify fake news in a wide range of linguistic circumstances [5].

Matheven and Kumar (2022) introduced a method utilizing deep learning and natural language processing (NLP) techniques for fake news detection. This approach likely leverages neural networks and linguistic analysis to identify misleading information [6]. Park and Chai (2023) focused on constructing a user-centered fake news detection model using classification algorithms in machine learning. Understanding user behaviors and preferences might offer enhanced accuracy in detecting misinformation [7]. Hayato, Yoshida, and Muneyasu (2022) presented a framework aiming to provide explainability for fake news detection methods on social media. The ability to explain the detection [5] process can improve trust and transparency in the detection models [8]. Rana et al. (2023) proposed compact BERT-based multi-models for efficient fake news detection. Compact models can offer resource-efficient solutions without compromising accuracy [9].

Guo, Lamaazi, and Mizouni (2022) explored smart edge-based fake news detection using pre-trained BERT models. Edge computing enables real-time analysis, crucial in rapidly identifying and addressing fake news at the source [10]. Hawashin et al. (2023) focused on improving Arabic fake news detection through optimized feature selection. Language-specific nuances require tailored approaches for effective detection in different linguistic contexts [11]. Alghamdi, Lin, and Luo (2022) discussed advancements in fake news detection, specifically on social media platforms. Analyzing social media content demands unique strategies due to the rapid dissemination of information and diverse communication styles [12].

III. Datasets

We collected Telugu news datasets from various news websites. Specifically, we gathered factual (Not-Fake) news from the telugu.hindustantimes.com website and fake, Misleading news from factly.in, includes almost all possible domains in the news website like business, sports, cinema, and many more. Scraping techniques were employed to retrieve data from these sites, extracting information such as news titles, authors, article descriptions, publication dates, times, and the news label (indicating whether the article was Fake, Not-Fake, or Misleading).

A. Preprocessing of Data

During preprocessing, our primary aim was to filter out irrelevant information, retaining only pertinent data. For instance, during the scraping process, extra symbols and unnecessary data were collected alongside the essential content. To refine the dataset, we eliminated these extra elements, keeping only the information essential for determining the factual accuracy of the news. Consequently, our preprocessed dataset includes attributes such as the article's headline (referred to as "claim"), a brief description of the claim's factuality, the article's factuality, the article's author, and the publication date and time.

After performing data collection and cleaning, we collected 2642 sentences categorized as Fake, 1906 as Not-Fake, and 706 labeled as Misleading from the factly.in website. We collected 3700 sentences categorized as Not-Fake. To balance the dataset, we reduced the number of Not-Fake sentences to 1906. Fig. 1, represents the label distribution of the dataset.

B. Analysis of the Balanced Dataset

Our final dataset comprises 4548 sentences, categorized into three classes: Fake (1906), Not-Fake (1906), and Misleading (736). Fig. 2, represents the snippet of the Telugu dataset.

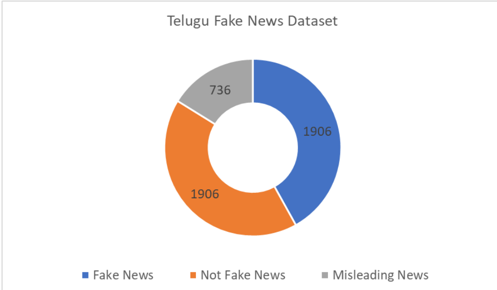

Fig. 1. Label Distribution

Claim	Fact	Fact-check	Reviewer	Date (YYYY-MM-DD)	Time
కమ్యూనిస్టు నేతగా ఇదివరకు జీవితాన్ని గడిపిన వి. ఎస్. అచ్యుతానందన్, ప్రస్తుతం నుదుటిపై తిలకం పెట్టుకొని దేవాలయాలను సందర్శిస్తున్నారు, దానికి సంబంధించిన ఫోటో.	ఈ ఫోటో మార్ఫ్ చేయబడినది. అసలు ఫోటోలో వి.ఎస్.అచ్యుతానందన్ నూదిటిపై తిలకం లేదు.	తప్పు	Dilip Kumar Sripada	2023-11-17	13:16:09
ట్విటర్‌లో ఉద్యోగాల కోత మొదలైంది. సగం మంది ఉద్యోగులు ఇక ఇంటి దారి పట్టాల్సిందేనని ట్విటర్ ఈరాత్రికి హెచ్చరించనుంది.	ట్విటర్‌లో ఉద్యోగాల కోత మొదలైంది. ఉద్యోగం ఊడితే ఆ సంగతి తెలుపుతూ ఆయా ఉద్యోగులకు కంపెనీ ఈమెయిల్ ద్వారా ఆ సంగతి తెలపనుంది.	నిజం	HT Telugu Desk	2022-11-04	11:29:00
ఇటీవల నల్లమల్ల అడవుల్లో తవ్వకాల్లో బయటపడిన శివలింగం యొక్క ఫోటో.	వాస్తవానికి ఈ శివలింగం జూన్ 2013లో అప్పటి నల్గొండ (ఇప్పుడు యాదాద్రి భువనగిరి) జిల్లాలో ఉన్న రాచకొండ కోట పరిసరాల్లో జరిగిన తవ్వకాల్లో బయటపడింది. ఇది రాచకొండ అటవీ ప్రాంతంలో ఉంది.	తప్పుదోవ	Varun Borugadda	2023-09-14	18:07:30

Fig. 2. Samples from Dataset

IV. Methodology

In the proposed model, we performed fine-tuning using mBERT, IndicBERT, XLM-RoBERTa, and MuRIL pre-trained models . The block diagram for the proposed model is shown in Fig. 3.

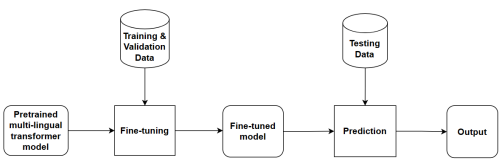

Fig. 3. Proposed Model

mBERT is a pre-trained multilingual BERT language model that is trained on more English text, mBERT is trained on more than 100 languages, including some low-resource languages. mBERT can be finetuned and adopted for specific small tasks. mBERT-Base has 12 layers of transformers that process long sequences of text, producing 768 numbers for each word or token in the text. It has a vocabulary of 30,000 tokens and 172 million parameters, capable of handling texts of up to 512 tokens in length.

XLM-RoBERTa is also a pre-trained multilingual language model, an upgraded version of BERT, trained on a large amount of text. It has a special feature that allows it to learn representations independent of language, making it effective at cross-lingual tasks. XLM-RoBERTa-Base has 12 layers of transformers, 768 hidden units each, and a vocabulary of 250,000 tokens and 270 million parameters. It can process texts of up to 512 tokens in length.

IndicBERT is also a multilingual ALBERT model, which is trained on large-scale corpora covering 12 major Indian languages. It has few number of parameters than other models like mBERT and XLM-R but still provides better performance on several tasks. IndicBERT is pre-trained with the IndicNLP corpus, covering 12 Indian languages (including English) with a total of 8.9 billion tokens. It is evaluated on IndicGLUE, a set of standard evaluation tasks used to measure the NLU performance of monolingual and multilingual models on Indian languages. IndicBERT-Base has 12 layers of transformers, 768 hidden units each, and a vocabulary of 110,000 tokens and 172 million parameters. It can process texts of up to 512 tokens in length.

MuRIL is also a BERT model pre-trained on 17 Indian languages and their transliterated counterparts. It is trained on around 9 billion tokens of novel corpus and evaluated on different tasks. MuRIL aims to address challenges related to Indian languages, such as spelling variations, transliteration, code-switching, and dialects. MuRIL-Base has 12 layers of transformers, 768 hidden units each, and a vocabulary of 110,000 tokens. It can process texts of up to 512 tokens in length.

We used 'Trainer' a high-level API provided by the HuggingFace library that facilitates the training and evaluation of transformer-based models. It streamlines the process of fine-tuning and training models on custom datasets by handling the training loop, data loading, and evaluation processes, TrainingArguments is a class that holds all the configuration options and hyperparameters for training a model using the 'Trainer'. It includes settings for the number of epochs, batch sizes, evaluation strategy, logging directory, learning rate, optimizer settings, model saving strategies, etc, AutoTokenizer is a class used for automatically loading the tokenizer associated with a particular pre-trained model. The AutoModelForSequenceClassification is a class used for automatically loading a pre-trained model suitable for sequence classification tasks. We used AutoTokenizer and AutoModelForSequenceClassification for both IndicBERT(ai4bharat/indic-bert) and MuRIL(google/muril-base-cased) pre-trained models, BertTokenizer and BertForSequenceClassification for loading tokenizer and model architecture of mBERT(bert-base-multilingual-cased), XLMRobertaTokenizerFast and XLM-RobertaForSequenceClassification for loading tokenizer and model architecture of XLM-RoBERTa(xlm-roberta-base).

V. Results

The experimental setup, results, and discussions for fine-tuning the models are discussed in this section.

A. Experimental Configuration

We fine-tuned pre-trained models for mBERT, XLM-RoBERTa, IndicBERT, and MuRIL utilizing the HuggingFace transformers library. The Fake news dataset was divided into training, validation, and testing datasets in the ratio of

80:10:10, for train, validation and test as shown in Fig. 4, with a learning rate of ”5e-5” with 3 and 5 epochs.

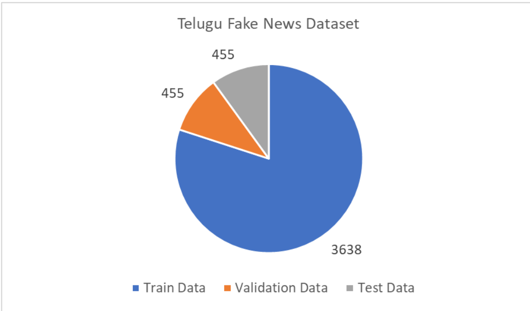

Fig. 4. Data Split Distribution

We set the batch sizes for both training and evaluation to 8 instances. Choose an evaluation strategy based on the number of epochs, for evaluating the model’s performance after each epoch. We specified the strategy for saving models at the end of each epoch with a limit of saving the best model only. Configured the model to load the best-performing model based on loss. Applied weight decay of 0.01 to prevent over-fitting. Incorporated a warm-up step of 500 to gradually increase the learning rate from a lower value. Presented training loss and validation loss while fine-tuning the models. Lower loss values typically indicate better performance.

mBERT: On 3 Epochs: From Fig 5, the training loss decreases from 0.467 to 0.318, and the validation loss decreases from 0.456 to 0.241 over epochs. This suggests the model is improving and generalizing well to unseen data. On 5 Epochs: From Fig 6, both training and validation loss decrease gradually over epochs, indicating continuous improvement in learning. The model seems to be learning more complex patterns as the training progresses.

XLM: On 3 Epochs: From Fig 7, the training loss decreases from 0.512 to 0.348, and the validation loss decreases from 0.923 to 0.272 over epochs. There’s a significant drop in validation loss, indicating better generalization in later epochs. On 5 Epochs: From Fig 8, initially, both training and validation loss increase slightly in the middle epochs but decrease towards the end, indicating some fluctuations in learning.

IndicBERT: On 3 Epochs: From Fig 9, the model shows a consistent decrease in both training and validation loss from 0.615 to 0.411 for training loss and 0.551 to 0.380 for validation loss, indicating effective learning. On 5 Epochs: From Fig 10, both training and validation loss continue to decrease, showing consistent improvement in the model’s performance.

Muril: On 3 Epochs: From Fig 11, the model exhibits a consistent decrease in both training and validation loss from 0.521 to 0.311 for training loss and 0.361 to 0.303 for validation loss, suggesting good learning. On 5 Epochs: From Fig 12, similar to IndicBERT, both training and validation loss continue to decrease, indicating further improvement in the model’s performance. Lower loss values typically indicate better performance.

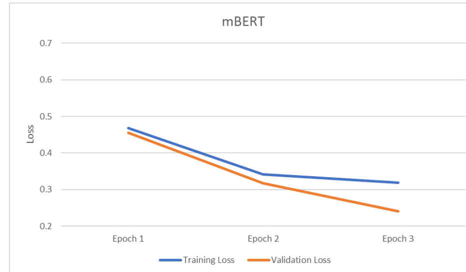

Fig. 5. Training & Validation Loss on mBERT for 3 epochs

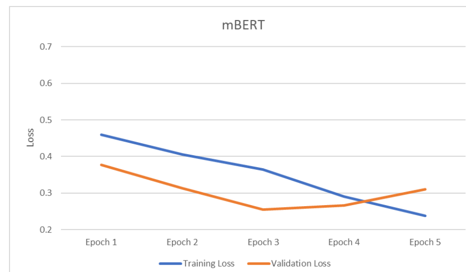

Fig. 6. Training & Validation Loss on mBERT for 5 epochs

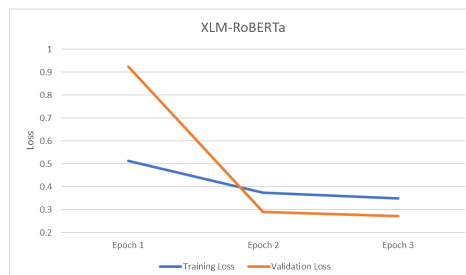

Fig. 7. Training & Validation Loss on XLM-RoBERTa for 3 epochs

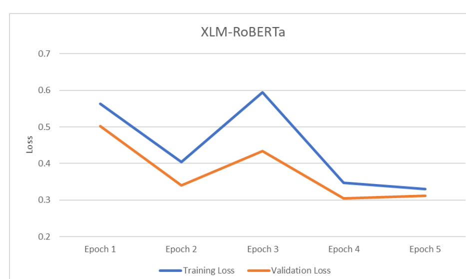

Fig. 8. Training & Validation Loss on XLM-RoBERTa for 5 epochs

B. Results and discussions

Initially, we fine-tuned our model by considering only one column from the dataset, i.e., ”Claim” and considered only

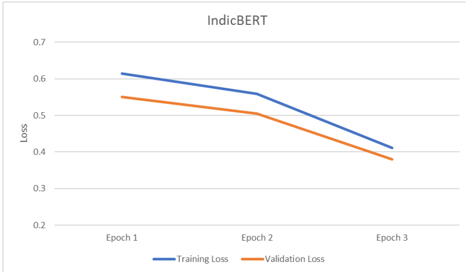

Fig. 9. Training & Validation Loss on IndicBERT for 3 epochs

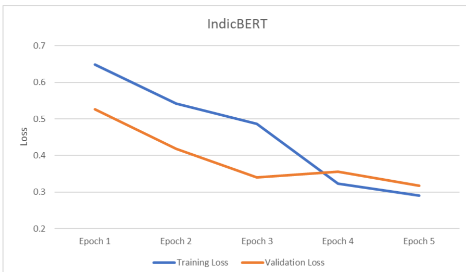

Fig. 10. Training & Validation Loss on IndicBERT for 5 epochs

two labels in the data, 'Fake' and 'Not-Fake' (we considered all the 'Misleading' news articles as "Fake"). The results of these implementations are represented in Table I.

TABLE I
PERFORMANCE METRICS OF MODELS

Epochs	mBERT	XLM-Roberta
3	95.37	94.29
5	92.74	95.67

From Table I, mBERT showed better performance when fine-tuned on 3 epochs, and XLM-RoBERTa showed better performance when fine-tuned on 5 epochs. Later we considered input data to the pre-trained models as two sentences which are news ("Claim" in our dataset) and explanation of the news ("Fact" in our dataset), and the labels are Fake, Misleading, and Not-Fake.

After fine-tuning the model on 3 epochs and 5 epochs, we tested the model on testing data, and used Accuracy and F1-score to compare our model's performance, these results

Fig. 11. Training & Validation Loss on MuRIL for 3 epochs

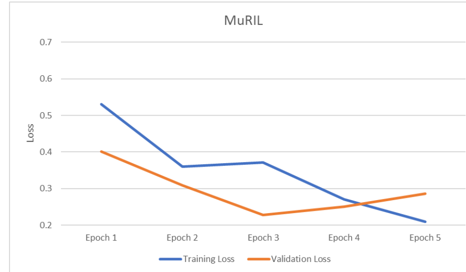

Fig. 12. Training & Validation Loss on MuRIL for 5 epochs

TABLE II
PERFORMANCE METRICS OF MODELS

	3 Epoch		5 Epoch	
Model	**Accuracy**	**F1-Score**	**Accuracy**	**F1-Score**
mBERT	88.79	87.90	87.69	86.42
XLM-RoBERTa	85.93	85.13	86.37	83.83
IndicBERT	81.31	80.10	86.81	86.71
MuRIL	88.79	88.57	87.25	84.81

are represented in Table II. **mBERT:** Achieved an accuracy of 88.79% and an F1-Score of 87.90% after 3 epochs, and 87.69% accuracy and 86.42% F1-Score after 5 epochs. **XLM-RoBERTa:** Recorded an accuracy of 85.93% and an F1-Score of 85.13% after 3 epochs, and 86.37% accuracy and 83.83% F1-Score after 5 epochs. **IndicBERT:** Showed an accuracy of 81.31% and an F1-Score of 80.10% after 3 epochs, and 86.81% accuracy and 86.71% F1-Score after 5 epochs. **MuRIL:** Achieved an accuracy of 88.79% and an F1-Score of 88.57% after 3 epochs, and 87.2% accuracy and 84.81% F1-Score after 5 epochs. Across the models, mBERT and MuRIL consistently maintain high accuracy and F1-Score. IndicBERT notably improves its performance from 3 to 5 epochs, showcasing significant accuracy and F1-Score enhancement. XLM-RoBERTa shows a slight improvement in accuracy but a slight decrease in F1-Score from 3 to 5 epochs.

Even though mBERT and MuRIL showed the highest overall accuracy, their performance was reduced on 5 epochs when compared to fine-tuning on 3 epochs. Our main focus is to improve the performance of the model on detecting misleading news, IndicBERT on 5 epochs and MuRIL on 3 epochs were able to predict 47 out of 75 misleading test data, as shown in Fig.13 and 46 out of 75 misleading test data as shown in Fig.14 respectively.

TABLE III
CLASS-WISE RESULTS OF INDICBERT ON 5 EPOCHS

Metric	Fake	Misleading	Not-Fake	Overall
Accuracy	0.89	0.63	0.94	0.868
Precision	0.82	0.71	0.98	0.868
Recall	0.89	0.63	0.94	0.868
F1-Score	0.85	0.67	0.96	0.867
Macro Avg	0.84	0.82	0.83	-
Weighted Avg	0.87	0.87	0.87	-

For IndicBERT on 5 epochs, the classification model achieved an accuracy of 88.79%. 'Not-Fake' demonstrated the

TABLE IV
CLASS-WISE RESULTS OF MURIL ON 3 EPOCHS

Metric	Fake	Misleading	Not-Fake	Overall
Accuracy	0.89	0.61	0.99	0.888
Precision	0.85	0.70	0.99	0.885
Recall	0.89	0.61	0.99	0.888
F1-Score	0.87	0.65	0.99	0.886
Macro Avg	0.85	0.83	0.84	-
Weighted Avg	0.88	0.89	0.89	-

highest precision, recall, and F1-score (99%), outperforming 'Fake' and 'Misleading'. Overall, the model exhibits reliable performance across the three classes with balanced precision and recall metrics as shown in Table III. For MuRIL on 3 epochs, the model achieved an accuracy of 86.81%. While 'Not-Fake' demonstrated the highest precision (98%) and F1-score (96%), 'Fake' had the highest recall (89%). Despite varying performances among classes, the model showed balanced metrics, with an overall sound performance as shown in Table IV.

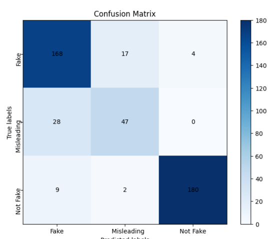

Fig. 13. Confusion matrix of IndicBERT fine-tuned for 5 epoch

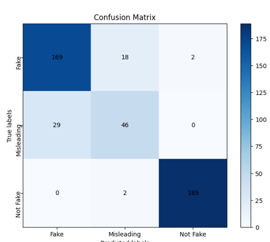

Fig. 14. Confusion matrix of MuRIL fine-tuned for 3 epoch

VI. CONCLUSION AND FUTURE SCOPE

In our study, we explored the detection of fake news in low-resource languages, primarily focusing on the Telugu language. Using various state-of-the-art transformer models like mBERT, XLM-RoBERTa, IndicBERT, and MuRIL to detect fake news in Telugu. We have concluded that mBERT and MuRIL are performing better with high accuracy and F1 scores for 3 epochs. IndicBERT showed improvement in the performance of the model between 3 to 5 epochs, significantly improving both accuracy and F1-Score. However, XLM-RoBERTa showed a slight improvement in accuracy but a decrease in F1-Score from 3 to 5 epochs. Although mBERT and MuRIL showed the highest overall accuracy, their performance decreased when fine-tuned for 5 epochs compared to 3 epochs. Both IndicBERT, fine-tuned for 5 epochs, and MuRIL, fine-tuned for 3 epochs, were able to classify more number misleading news correctly.

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