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Sarcasm Detection In News Headlines Using ML And DL Models

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Abstract- *Sarcasm is a form of language defined using words or phrases that express the opposite of their actual meaning, often with a purpose of mocking or criticizing something or someone. Sarcasm detection is crucial for false news detection, opinion mining, sentiment analysis, detecting cyberbullies, online trolls, and other similar activities. Detecting Sarcasm is a part of Sentimental Analysis. This paper focuses on analysis of news headline to detect sarcasm using ensemble Machine Learning models like XGBoost,AdaBoostand Deep learning models like BiLSTM, CNN,RNNand a Hybrid CNN and BiLSTM model. The RNN model outperformed all of the other models with an accuracy of 0.79 and balanced F1 score of 0.76, which indicates its proficiency in discerning sarcastic content. LIME analysis is implemented to evaluate contribution of each word in a news headline towards sarcasm.*

IndexTerms –News Headline, Sarcasm, Tokenization, LIME

I. INTRODUCTION

Natural Language Processing (NLP) in AI aims to empower computers to comprehend, translate, and generate human language. It encompasses a variety of tasks like as sentiment analysis, named entity recognition, text categorization, and audio recognition. NLP is used in many different fields, including language translation services, chatbots, virtual assistants, and text summarization. Due to its ability to process and analyse large amounts of unstructured text input, NLP[1] is an essential technology for enhancing human-computer interactions in a variety of industries. As a result, advances have been made in the automation of processes including information retrieval, content creation, and customer support. Sarcasm is the utilisation of language in a funny or critical way to state something simple but really meaning something very different. Understanding sarcasm in news headlines might help readers avoid misinterpreting what is being said. Recognising sarcasm [3] in news headlines is a difficult problem, but modern innovations such as machine learning (ML), NLP, and deep learning(DL) offer an appropriate solution. These sophisticated computational techniques can be used to precisely detect instances of sarcasm in news headlines by analysing emotions, contextual signals, and language patterns. Sarcasm is a language strategy that is frequently used for humor, irony, or satire. It involves using words to convey something other than their literal meaning. Sarcasm in news headlines poses a problem since it might cause readers to misunderstand or become confused, which could impair their comprehension and impression of the news. The challenge is in recognizing and differentiating between real and humorous news headlines. Identifying sarcasm in news headlines is essential to avoiding misunderstandings and guaranteeing that readers understand the intended message.Detecting sarcasm in news headlines is a challenging yet essential task within the field of NLP, and various ML and DL play an important role in resolving this complexity. Sarcasm, which includes presenting concepts in a way that contradicts their literal meaning, requires an extensive understanding of linguistic complexities. DL play a crucial role in various applications, including sarcasm detection in news headlines. These models excel in capturing complicated patterns and contextual details in language, allowing them to identify hidden signals indicating sarcasm.

This paper focuses on the classification of news headlines into non-sarcastic and sarcastic categories. Prior to classification, the dataset undergoes preprocessing. Ensemble Machine learning models like XGBoost, AdaBoost and Deep learning models like BiLSTM, CNN, RNN and a Hybrid CNN-BiLSTMwere used to train the dataset and then LIME analysis [4]has been applied to understand the contribution of each word in a news headline.

Key contributions of this paper are:

- Comparative analysis of various deep learning and machine learning classification algorithms for news headline classification.
- LIME analysis is applied to identify the key words contributing to the detection of

sarcasm.This study is divided into distinct sections, each with a specific purpose. The "Related Work" section reviews existing literature and research efforts in sarcasm detection, highlighting diverse approaches and models employed in various domains. The "Data Set Description" outlines the dataset used for the study, detailing its attributes and origin. The "Methodology" section comprehensively explains the data preprocessing steps, feature engineering techniques involving machine and deep learning models, model training, evaluation metrics, and the incorporation of LIME analysis for interpretability. The "Result & Analysis" section presents the outcomes, including data visualizations, hyperparameter tuning results, and the performance evaluation of different models. Finally, the "Conclusion" summarizes key findings,and proposes avenues for future work in advancing sarcasm detection methodologies in news headlines.

II. Related Work

Detecting sarcasm in news headlines is a challenging yet crucial task in understanding language. This section covers a wide range of sarcasm detection domains by employing advanced ML and DL models in news headlines, social media, and bilingual settings. Approaches include CNN-LSTM models, sentiment analysis intersections, and novel ensemble techniques for learning, all aimed at improving accuracy. It highlights how sarcasm detection techniques have developed and become more applicable, highlighting the multidisciplinary aspect of linguistic studies in contexts ranging from news to social media.

Mandal et al.[5]proposed a CNN-LSTM model for sarcasm detection with 86.16% accuracy, consisting of a CNN, bidirectional LSTM, and word-level vector encodings. The NLTK package was used for data preprocessing, including creating a frequency list and applying word tokenization and stemming.Misra et al.[6]. presented an extensive dataset comparing satirical and authentic news headlines for sarcasm detection, offering a hybrid neural network design. Using TheOnion and HuffPost data, word clouds illustrate distinct terms, emphasizing the dataset's advantages in formal language and labeling quality.Zanchak et al. [7]achieved high sarcasm detection accuracy using BiLSTM, RNN, CNN, and ensemble models. Pre-processing involved removing stop words, digits, and punctuation, while TF-IDF extraction with Bayesian classifiers and logistic regression boosted accuracy, addressing challenges in obtaining correctly labelled training data and detecting polarity.

Barhoom et al.[8] investigated the link between sarcasm detection and sentiment analysis, employing classifiers and neural networks on diverse datasets. Previous studies used deep convolutional neural networks and BERT,achieving accuracies of 86.16% and 92%. The use of a news headlines dataset with formal language and high- quality labelling sets this work apart from methods relying on noisy Twitter data.Lahaji et al.[9] contributed to sarcasm recognition by selecting effective strategies from past research for web-based detection in news headlines. Their recommended approach analyses word semantic properties and headline structure to successfully differentiate between sarcastic and non-sarcastic language. To ensure system quality, data pre-processing was crucial, and GridSearchCV was utilized to train models with optimal hyperparameter values, emphasizing achieving or surpassing human analysts' baseline agreement of 80-85% in sentiment score system training.

Bingöl et al. [10] classified sarcasm into categories like failed expectations and stylistic elements. The paper explored study methods for sarcasm detection, including eye movement data and language traits. Techniques for identifying sarcastic terms in social networks are evaluated using measures like F-measure, accuracy, precision, and recall.Novic et al. [11] used a polynomial kernel SVC model for sarcasm detection in news headlines, compared its accuracy with logistic regression and a dummy classifier. As a master's thesis at the City University of New York, the study aimed to identify sarcasm, providing insights by comparing results with a baseline model in linguistic research.

Liu wet al. utilized[12]a Kaggle dataset, renowned for lower noise levels and sourced from reliable outlets like The Onion and Huff Post. Shifting away from social networking site data for sarcasm detection, author demonstrated the success of the BERT-LSTM model on news headlines, leveraging its expert and low-noise qualities. The study suggested broader applications beyond news, indicating potential usefulness in tweet and image sarcasm detection. Lie et al. [13] enhanced sarcasm identification in mixed English and Chinese social media using a novel Multi-Strategy Ensemble Learning Approach (MSELA) with customized features. The study compared performance against a unique multi-strategy algorithm, emphasizing unbalanced datasets and incorporating the "semantic imbalance rate" for context inconsistencies. Additionally, it explored distinctive Chinese features, evaluating model effectiveness across English and Chinese corpora using the AUC metric.

In conclusion, this section emphasizes the importance of high-quality datasets and tailored methods for accurate sarcasm detection in news headlines. This proposed model experiments deep learning and machine learning models to arrive at the best model for sarcasm detection.

III. Data set Description

The dataset "*Sarcasm Detection in News Headlines*" is obtained from Kaggle[1]and it comprises of 28,619 records. It contains three attributes. The first attribute, "Is Sarcastic," which decides whether the headline is sarcastic or not. This serves as the target variable for the classification task, indicating the presence of sarcasm in the news headline. The second attribute, "Headline," includes the actual text of the news headlines, encompassing a range of different headlines. The third attribute, "Article Link," provides the reference or link to the specific news article associated with each headline.

IV. Proposed Methodology

The methodology section includes Data collection, Data preprocessing, Model training, Model evaluation, and LIME Analysis as shown in Fig. 1.

Data Preprocessing

The data preprocessing begins with a series of steps aimed at ensuring data integrity. The basic steps include dropping unnecessary columns, text normalization, tokenization, Lemmatization. As the *article_link* column is not necessary, article_link column is dropped. The duplicated instances are dropped and series of text normalization steps were performed. This involves converting all text to lowercase, removing non-alphabetic characters like punctuation and numbers, tokenizing sentences, lemmatizing words[14], and eliminating common English stop words.

Feature Engineering

The text data is word tokenized, a process that includes converting text sequences to integer sequences based on the tokenizer's vocabulary and Word2vec embedding[15] and then padding sequences to a defined length so that it can be an input into neural networks that require uniformly sized inputs.

For Machine learning models, Bag-of-Words approach converts text to numerical features based on word frequencies per document, with no respect for word order. In scikit-learn, Count Vectorizer [16] takes this method by tokenizing text, generating a word vocabulary, and translating data into Document Term Matrix (DTM). The goal was to ensure uniformity, reduce noise, and transform the text into a more analysable and standardized format, thereby enhancing the quality of the dataset for subsequent analysis or modelling tasks in natural language processing.Model training

In Model training six different Machine and Deep learning models AdaBoost, XGBoost, BiLSTM, CNN, RNN and a Hybrid CNN-BiLSTM model are implemented.

AdaBoost

AdaBoost is a supervised ensemble ML model that sequentially combines weak classifiers, adjusting weights to prioritize misclassified instances. Through iterative boosting, it creates a strong classifier by weighted voting, focusing on difficult instances in subsequent training steps.

XGBoost

XGBoost is a supervised ML model. It is an ensemble model. It a revised gradient boosting technique,[17]builds decision trees sequentially, correcting errors and employing regularization for efficient ensemble learning. Through iterative fitting of new trees to residuals, it creates a robust, scalable model with fine-tuned predictions.

CNN

CNNs are deep learning models[18]. These models utilize convolutional layers to learn patterns hierarchically, recognizing features at different levels, and pooling layers to minimize spatial dimensions. This architecture enables independent feature extraction, enhancing the effectiveness of CNNs. The [19] CNN that was built has sequential layers that are tuned for text classification. The CNN for text classification includes layers like Embedding, Conv1D with ReLU activation, MaxPooling1D, Flatten, and Dense with sigmoid activation, leveraging convolution and pooling for complex text representation and dense layer for classification.

Bi-LSTM

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Bi-LSTM, excelling in modelling sequential data, utilizes two Bidirectional LSTM layers [20]for effective capture of contextual information in both forward and backward directions. With an Embedding layer for word-to-vector conversion and a final Dense layer with sigmoid activation for binary classification, this architecture employs Bidirectional LSTMs and embeddings to understand bidirectional sequences and complex text patterns for efficient categorization.

RNN

RNNs, specialized for sequential data analysis, use recurrent connections to maintain memory and analyze information hierarchically, making them effective for tasks like time series prediction and language modeling. The architecture for text analysis includes an Embedding Layer for contextual interpretation, a Simple RNN Layer with 64 units to identify sequential patterns, and a Dense Output Layer for binary classification, emphasizing sequential understanding in sarcastic class prediction.

Hybrid CNN BiLSTM Model

The CNN-BiLSTM hybrid model combines CNNs' feature extraction with Bi-LSTMs' sequential understanding for text tasks. The architecture includes a Conv1D layer with 32 filters and ReLU activation for feature extraction, followed by MaxPooling for dimension reduction. Two BiLSTM layers capture bidirectional sequential input, leading to further layers with a Dense layer (64 units, ReLU), a Dropout layer (dropout rate of 0.5), and an output Dense layer with sigmoid activation for binary classification. This hybrid architecture captures varied patterns in input sequences, emphasizing both local and global features.

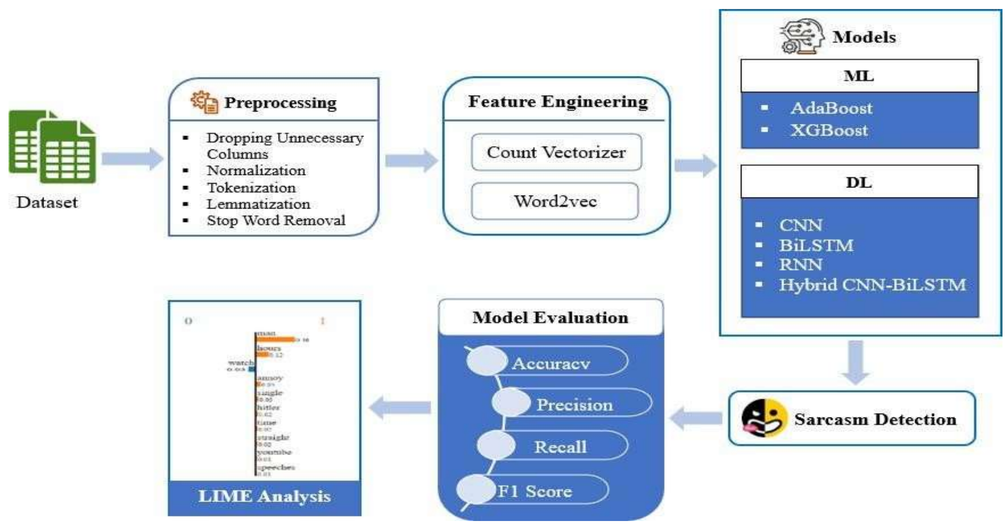

Fig. 1 Proposed methodology for Sarcasm detection on textual data

Model Evaluation

IV. RESULT & DISCUSSIONS

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The model is assessed based on evaluation metrics like Accuracy, F1 Score, Precision and Recall.Evaluation metrics like accuracy provide an overall measure, precision emphasizes the relevance of positive predictions, recall focuses on capturing all actual positives, and F1-score balances precision and recall, collectively ensuring a comprehensive assessment of the model's performance.

Explainable AI

Lime analysis is used to explain machine learning and deep learning model predictions by producing understandable and locally accurate insights for specific occurrences. It dissects complex model decisions, providing feature importance by affecting input features, and assisting in understanding the behaviour of black-box models for various tasks such as text classification or image recognition.

LIME Analysis was conducted on the model that achieved the highest accuracy i.e. RNN model. This analysis serves to provide insightful explanations for the RNN model's predictions, aiming to understand how and why the model predict a news headline as sarcastic or not.

Data Visualization

The purpose of data visualization is simplifying complex information which enables clear understanding of the patterns. Data visualization in sarcasm detection involves creating graphical representations of linguistic patterns and contextual cues, enabling a clearer identification of sarcastic elements in textual data, thereby enhancing the accuracy of sentiment analysis models.

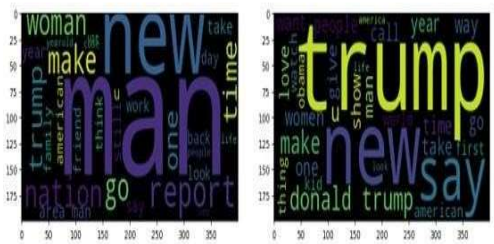

Fig.2 Sarcasric and Non-Sarcastic Wordcloud

The word cloud of sarcastic and non-sarcastic words is shown in Fig. 2. Words like „man", „new", „make" are more sarcastic and words like „trump", „say" are shown to be non-sarcastic.

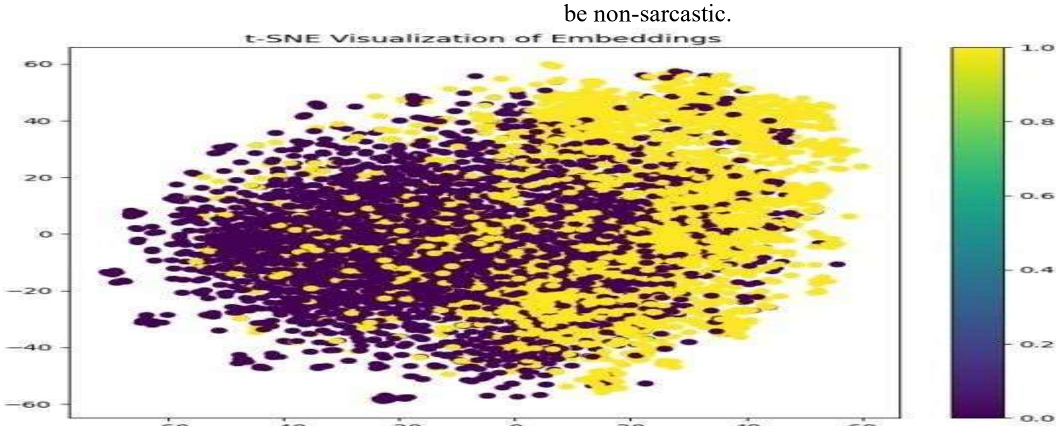

Fig. 3 t-SNE visualization of RNN model

Table I. Variation in Parameters Before and after Hyperparameter Tuning

Models		Hyperparameter Tuning Before	After	Accuracy %
CNN	Filters	16	32	79.49
	Kernel size	3	5	
BiLSTM	1st -No. of Units	16	32	79.34
	2nd -No. of Units	16	128	
RNN	No. of units	16	128	79.88
	Batch size	16	128	
Hybrid	Filters	16	32	
	Kernel size	3	5	
CNN-BiLSTM	Filters	5	10	78.53
	Kernel Size	5	10	

T-SNE visualisation is a data analysis approach that represents high-dimension data points in a lower- dimensional space.It is especially helpful in analysing and interpreting high-dimensional information, exposing patterns and clusters that may not have been visible in the original data space. The Fig. 3 depicts a two-dimensional scatter plot of text data points, with each point representing a word. The colours of the points indicate sarcastic or non-sarcastic. The sarcastic cluster appears to be more distributed than the non-sarcastic cluster. This could be because sarcastic language is more varied and context-specific than non-sarcastic language.

Hyperparameter Tuning

Hyperparameter tuning was performed on various Deep Learning models as shown in TABLE I. This led to an improvement in accuracy across all models. But when

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compared to other models CNN and RNN benefited from increased filters and units, improving accuracy. In contrast, BiLSTM accuracy slightly decreased, and thehybrid CNN-BiLSTM showed a decline despite hyperparameter adjustments.

Results of Model Performance

Classifiers	Accuracy %	Precision	Recall	F1 Score
AdaBoost	66.61	0.78	0.39	0.52
XGBoost	73.00	0.79	0.56	0.66
CNN	79.49	0.77	0.78	0.78
BiLSTM	79.34	0.77	0.77	0.77
RNN	79.88	0.83	0.70	0.76
Hybrid CNN-BiLSTM	78.53	0.76	0.77	0.77

TABLE II. PERFORMANCE OF THE CLASSIFIERS

The evaluation of six distinct machine learning and deep learning models is performed using evaluation metrics like Accuracy, F1-Score, Precision and Recall. The Machine learning models include AdaBoost, XGBoost and deep leaning models include BiLSTM, RNN,CNN and a Hybrid CNN BiLSTM model. The efficiency of these models have been presented in TableII.

The RNN model has achieved the highest accuracy of 79.88% as shown in Table 1. Its precision score of 0.8388 displayed its ability to make highly accurate predictions. Furthermore, with a recall rate of 0.7029, the RNN performed well in effectively identifying and gathering relevant instances, showing its ability to identify true positives. This model's balanced F1 score of 0.7648 demonstrates its ability to find a harmonic balance between precision and recall.

BiLSTM, Hybrid CNN-BiLSTM andCNN models also performed well with accuracies of 79.49%, 79.34% and 78.53% respectively. Adaboost and XGBoost performed below expectations, with accuracies of 66.61% and 73.00%, respectively. By observing the performance of all models, Deep Learning Models performed better than ML models in terms of overall performance.

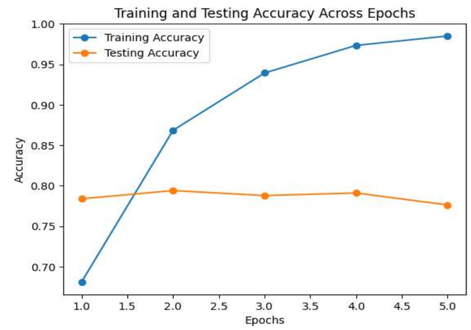

Fig. 4 Accuracy of Training and Testing data acrossEpochs

Fig.4 plots the training and testing accuracies for RNN model with respect to number of epochs.The training accuracy steadily improves from 0.56 in the first epoch to approximately 1.0 by the fifth epoch, indicating effective learning from the training data as shown in Fig. 4. In contrast, testing accuracy shows fluctuations, starting at 0.78 in the first epoch, decreasing in the second, increasing after the third, and then declining after the fourth, settling around 0.77 by the fifth epoch. The consistent gap of 0.05-0.2 between training and testing accuracy suggests potential overfitting, where the model fits the training data too closely, hindering generalization. To address this, adjustments in model complexity orhyperparametric tuning can be done. The steady increase in training accuracy indicates model convergence, while testing fluctuations suggest sensitivity to data variations. Analyzing optimal epochs helps identify when the model generalizes the test data properly.

Explainable AI

Now let's consider one sample instances of sarcastic. For sarcastic sentiment instance, the text reads, “annoy youtube algorithm let man forget single time watch hours straight hitler speeches” as shown in Fig. 5. From the text, it can be seen that it is sarcastically saying that once any YouTube video is seen,

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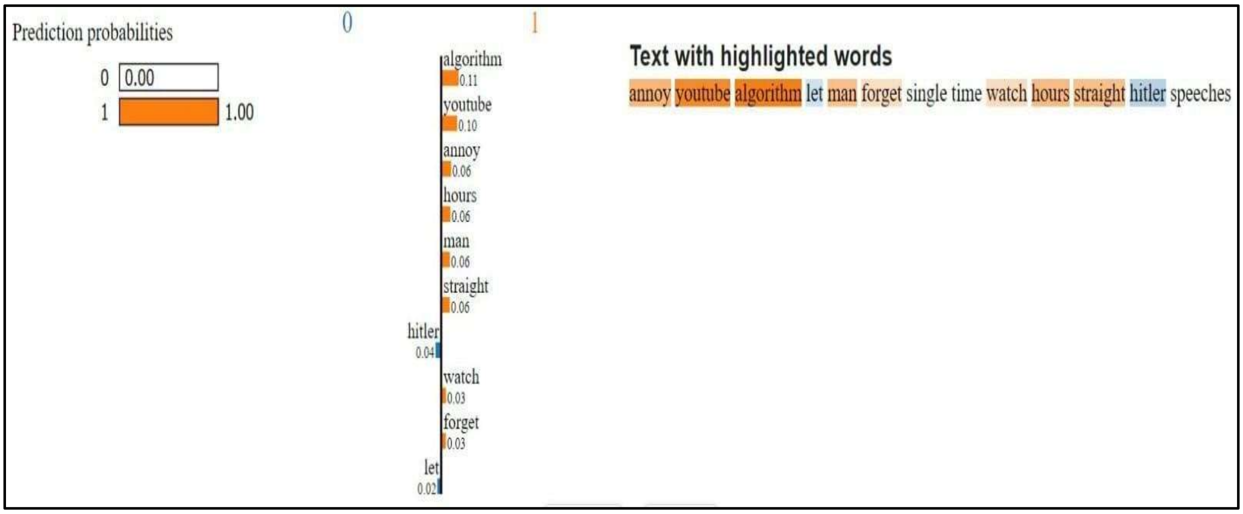

Fig. 5Prediction for a Sarcastic Instance in LIME Analysis

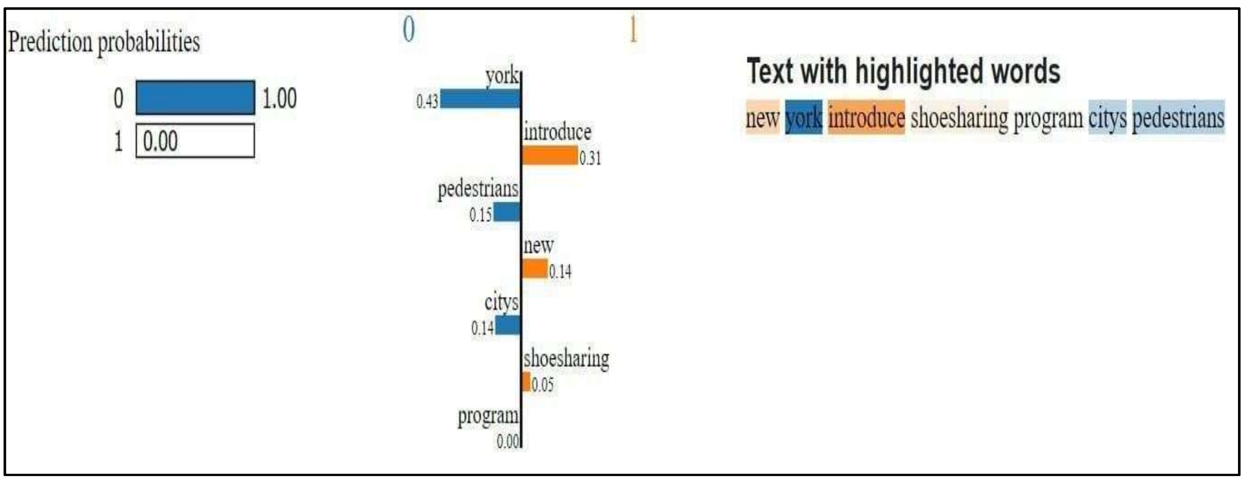

Fig.6 Prediction for a Non Sarcastic Instance in LIME AnalysisYouTube algorithms are making people see the same videos as Hitler's speeches. The word „man" contributed more to sarcastic which can be seen in wordCloud Fig. 4, model was able to identify it. Here the words „man" and „hitler speeches" are not meant man and hitler speeches in a literal sense it is of mankind and videos that are coming continuously like hilter speeches, which the model was able to interpret and predict as sarcastic.

After considering a non-sarcastic instance with the text: "New York introduces a shoesharing program for the city's pedestrians". Despite the possibility of a sarcastic interpretation, implying a mocking tone toward the difficulty of sharing shoes in a busy and fast-paced city like New York, the model predicts this instance as shown in Fig. 6 as non-sarcastic.The text is incorrectly predicted as the text is sarcastic but it is predicted to be non-sarcastic.

The difference is due to the normalization process applied in the code. LIME explains the instance by creating an interpretation for each feature in the text. Each interpretation consists of a local feature and its weight. The local feature is a token, and the weight is a number that reflects the contribution of that token to the prediction. However, LIME also considers a baseline distribution for the tokens in the text. This baseline is typically created by shuffling the original dataset. Therefore, each interpretation in LIME actually contributes to the final prediction score of the text, and this contribution may vary due to the shuffling of the dataset. The normalization process applied in the code sums up all the interpretation weights (the second column in the output of explanation.as_list()) for each instance. This sum is then divided by the original prediction probability (the first column in the output of explanation.as_list()) to get the normalized prediction probabilities. Since LIME also considers a baseline distribution, the final normalized prediction probabilities may not match exactly the sum of the LIME explanier ai's probabilities values. This is because the normalization process includes a correction factor due to the difference in prediction scores between the original instance and the baseline instance.

In conclusion, the model showed inconsistent results in differentiating between sarcastic and non-sarcastic occurrences. It was able to recognise the sarcasm in the YouTube algorithm example, but it had trouble with the non-sarcastic example about the shoesharing program in New York. The last example, which may be taken as sarcastic, was incorrectly predicted as non-sarcastic, demonstrating that the model might struggle to catch the sarcastic tone in certain situations. The model gets it right approximately 79% of the time. The text is incorrectly predicted as sarcastic but it is non-sarcastic according to dataset.

V.CONCLUSION

In conclusion, this research paper delves into sarcasm detection in news headlines using a diverse set of machine learning and deep learning models. Through meticulous data preprocessing, including text normalization and word embedding, the study explores six models, ranging from ensemble machine learning (AdaBoost, XGBoost) to deep learning architectures (CNN, BiLSTM, RNN, Hybrid CNN-BiLSTM). Notably, the RNN model emerges as the most effective, achieving an accuracy of 79.88% and a balanced F1 score of 0.7648. The incorporation of LIME analysis enhances interpretability, providing insights into the decision-making processes of the models, with a focus on RNN. However, it suggests that there's still a room for improvement in handling the complexities of sarcasm detection.

Future work could involve refining the interpretability of deep learning models, exploring larger and more diverse datasets, and investigating real-time applications for improved sarcasm detection in evolving news landscapes. Additionally, the exploration of SHAP (SHapley Additive exPlanations) analysis could be considered, offering further insights into the model's feature importance andcontributing to a more comprehensive understanding of sarcasm detection dynamics. This research contributes to advancing sarcasm detection methodologies in news headlines, offering potential insights for refining sentiment analysis and understanding the nuanced linguistic dynamics within media discourse.

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