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Research Article

A Hybrid Feature Selection Method to Detect Sarcasm in Telugu Text Leveraging AdaBoost Classifier.

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ABSTRACT

Automatic sarcasm detection refers to the process of predicting sarcasm inside text. The ubiquity and complexities of sarcasm in sentiment-laden text represent a crucial stage in numerous sentiment analysis endeavours. Every day, individuals worldwide utilize social media platforms to disseminate their opinions, experiences, and suggestions. Sarcasm is often employed in newspaper headlines to capture readers' attention. Consequently, the necessity for a system capable of automatically and consistently detecting sarcasm has become paramount. Low-resourced and morphologically rich languages, such as Telugu, have garnered considerable attention from scholars. In Telugu sarcasm can be represented using proverbs, repeating the same word multiple times and also mentioning ellipses. In Telugu, sarcasm can be conveyed through proverbs, the repetition of words, and the use of ellipses. Leverage neural networks to create sarcasm detectors and investigate the methods by which a machine might learn sarcastic patterns. This research analysed hybrid feature selection utilizing the Gini index and entropy in conjunction with the AdaBoost machine learning classifier to enhance its performance.

Keywords: Sarcasm, AdaBoost classifier, Telugu language, Deep Learning

1. INTRODUCTION:

Sarcasm is a type of linguistic irony in which an individual articulates a statement that conveys the contrary meaning, typically with the intent to ridicule or elicit comedy. It is essential to human communication; however, it can be challenging to discern, particularly in written material absent of tone and facial expressions. Twitter is a widely utilized platform for individuals to express their perspectives, articulate their beliefs, and report events in real time [1]. Dane and Greenwood Demonstrated that the inclusion of sarcastic language can significantly enhance the efficacy of sentiment analysis. Effective sarcasm detection necessitates adequate training in learning models. Numerous studies have been conducted on the expression of sarcasm, including its motivations, timing, and mechanisms [2]. The majority of Telugu-speaking users on social media commenced communicating in their own language [3]. The analysis of the sent text will be enhanced by employing an automated sentiment analyser that incorporates a sarcasm detection methodology. For example, “Wow, you’re such a genius for locking yourself out of your own house.” Creating an annotated dataset in a low-resourced language presents a significant challenge for researchers.

2. RELATED WORK:

Saifullah Razali et al. extracted features from CNN architecture which are manually built, are classified using logistic regression and evaluated with performance criteria through comparative analysis [4].

Yashvardhan Sharma et al. offered an analysis of many language datasets from twitter of differing sizes and employed machine and deep learning techniques to examine the performance of diverse languages and code-mixed datasets in order to identify an appropriate classifier [5]. *Yufeng Diao et al.* presented a Multi-dimensional QA system to identify ironic *on English sentences [6*]. mainly focused on semantic representations to catch the controversial sentences. Their finding shows the Bidierctional LSTM model with attention mechanisms to detect the humour in QA based networks.

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Muhammad Ehtisham Hassan et al. Developed a hybrid methodology for Urdu sarcasm. Primarily due to social media, a substantial amount of data has been collected, serving as a platform for communication and message dissemination. Their research findings shown strong performance in low-resource languages. These strategies can be applied to different linguistic datasets. BERT delivers optimistic solutions. showcases a newly annotated dataset of Urdu sarcasm comprising 12,910 tweets [7]. Benchmark outcomes with deep learning algorithms. mBERT with Bi-LSTM was employed to achieve enhanced performance.

Mochamad Alfan Rosid et al. constructed a mixed coding dataset comprising Indonesian and English texts. Created an innovative hybrid model utilizing distinct pre-trained word embeddings for two different languages, specifically GloVe and FastText [8]. This hybrid model integrates CNN with a multi-head attention mechanism and BI-GRU to attain promising results.

Le Hoang Son et al. Automatic sarcasm identification focuses on the utilization of lexical, syntactic, or pragmatic aspects that are frequently articulated using symbolic literary techniques [9]. Proposed a hybrid model, sAtt-BiLSTM, integrating CNN. The dataset, comprising both balanced and uneven samples, was compared across various classifiers, with their hybrid model yielding remarkable results. GloVe utilized as a universal word embedding for the dataset.

S. Muhammad Ahmed Hassan Shah et al. worked on Arabic language to detect sentiment in sarcasm intrinsic text. Proposed Modified Switch Transformer for sarcasm, dialect detection [10]. The switch transformer model employs probabilistic projections through a Variational Spatial Gated Unit-MLP to improve the embedding generation process.

Abdul Sami et al. This research assesses BILSTM, GRU, and LSTM inside a Federated Learning (FL) framework, revealing that BILSTM surpasses the others in F1 score [11]. The incorporation of attention processes significantly improves performance by concentrating on contextually pertinent material. The primary goal of federated learning is confidentiality of data. On users' devices can train and run the model.

Yufeng Diao et al. wants to differentiate the sarcasm and humor [12]. Proposed two tasks for each identification via a multi-task technique. Typically, these two activities must collaborate to discern humor. Their research collected semantic attributes for each task to enhance the performance of deep learning models.

Aytug Onan et al. introduces a robust framework for sarcasm detection on social media utilizing neural language models and deep neural networks [13]. An innovative inverse gravity moment-based term weighting model utilizing trigrams improves text representation by emphasizing essential terms while maintaining word order. A three-tier stacked BiLSTM architecture is utilized for sarcasm identification, assessed on three sarcasm datasets.

Aruna Bhat et al. developed a deep learning framework for multimodal sarcasm detection [14]. This study improves sarcasm recognition by integrating multimodal data, including both textual and visual clues. An innovative architecture utilizing RoBERTa with a co-attention layer effectively captures contextual incongruence between textual and visual features. Text features are derived using GRU, whilst picture features are handled via Feature-wise Linearly Modulated ResNet Blocks.

Axel Rodríguez et al. designed new framework SINCERE which is graph-based approach [15]. It derives latent representations and improves sarcasm identification through sentiment and emotion analysis. Their findings shows that it is more effective for a restricted set of annotated data.

3. METHODOLOGY:

3.1 Dataset:

The dataset is manually annotated by linguistic experts in the field. Each sentence is annotated with a label indicating sarcasm or its absence. The dataset has a total of 6,500 sentences collected from comments on humorous Telugu shows and news headlines. The dataset comprises Telugu utterances that feature proverbs like "కానీ అది పాత చింతకాయ పచ్చడిలా ఉండటంతో జనాలు తొలి షోతోనే పెదవి విరిచేశారు.", repetitions, and ellipses to denote

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sarcasm. Out of 6500 sentences, 3000 are sarcastic, while the remaining 3500 are non-sarcastic. Some of them is shown in table 1.

Telugu sentences	English translation	Label
గెలిచినందుకు కాదు... పొట్టి చేసిన ప్రతిసారి ఒడిపోయి గిన్నిస్ బుక్ లో ఎక్కడంటా!!	It's not because of winning... Every time I do it short, I fall down and get into the Guinness book!!	Sarcasm
కొండనాలుకకు మందు వేస్తే ఉన్న నాలుక ఊడిందన్న సామెత ఆ యువకుడి విషయంలో నిజమైంది.	The saying that if you give medicine to a hillbilly's tongue, the tongue will be blown, was true in the case of that young man.	sarcasm
సిక్సర్లు బాదారని ఏడ్చిన కుల్దీప్.	Kuldeep cried because the sixers are bad.	Non-sarcasm
తిరుపతి సమీపంలోని కల్యాణి డ్యామ్‌ను టిటిడి తిరుపతి జెఈవో బి లక్ష్మీకాంతం అధికారులను ఆదేశించారు.	Kalyani Dam near Tirupati TTD Tirupati JEO B Laxmikantham directed the officials.	Non-sarcasm
విండీస్ ఏ దశలోనూ పోటీ ఇవ్వలేక చాపచుట్టేసింది...!!	Windies could not compete at any stage...!!	sarcasm
గంటల తరబడి క్యూలో నిలబడటం నాకు ఇష్టమైన హాబీ ....!!!	standing in queue for hours is my favorite hobby......!!!	sarcasm

Table 1: Sarcasm Telugu sentences with English translation

The systematic work flow of the proposed model is illustrated in figure 1.

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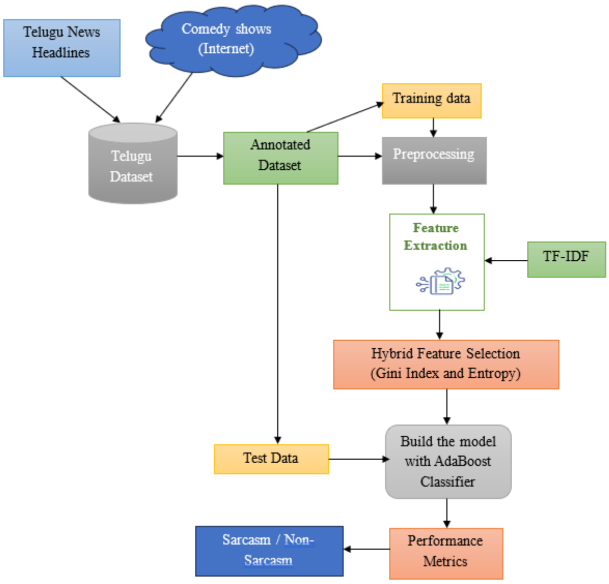

Figure 1: Workflow of the Telugu sarcasm detection

3.2. Pre-Processing:

Converting text into a format comprehensible to an algorithm is a complex endeavour. This section outlines the procedures involved in text processing [15].

i) Tokenization: Superfluous tokens can be readily eliminated, as a document is converted into paragraphs or phrases into individual words.
ii) Elimination of Irrelevant Tags and Punctuation: The subsequent phase is the removal of punctuation, as it does not contribute additional information while processing text data.
iii) Eliminating stop words: Commonly used terms that lack distinct semantic value
iv) Lemmatization: An alternative method for eliminating inflection by identifying the portion of speech and use an extensive linguistic database.

The pre-processed data are currently undergoing feature extraction to classify based on these features.

3.3. Feature Extraction:

TF-IDF (Term Frequency-Inverse Document Frequency) is a statistical metric employed in Natural Language Processing (NLP) and text mining to assess the significance of a word inside a document in relation to a corpus of documents [16]. It facilitates the conversion of unprocessed text into numerical feature vectors, rendering it advantageous for machine learning models.

$$\boldsymbol{TF}(t,d) = \frac{No.of\ Times\ 't'\ appears\ in\ a\ document}{Total\ no.of\ Terms\ in\ a\ document\ 'd'} \quad (1)$$

Term Frequency (TF) is calculated as the frequency of a specific occurrence or keyword in a document divided by th e entire word count of that document represented in equation (1)

$$IDF = log \in \frac{Total\ No.of\ documents\ d}{No.of\ documents\ that\ contains\ term\ t} \quad (2)$$

Inverse Document Frequency (IDF) denotes the significance of a phrase inside a collection of documents. The IDF computes the significance of infrequent terms within a document corpus. It can be seen in equation (2)

3.4. Feature Selection:

The feature selection method is conducted to identify the subset of terms that appeared during training and these selected subsets are utilized as features for text categorization. A target value must be determined for a specific set of

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features. Instances and features must be taken based on the root word to initiate the splitting process. Consequently, there arises a must to assess the informativeness of features and utilize the most informative feature for data partitioning. Informativeness is assessed by information gain, necessitating an understanding of entropy within the dataset. Initially, the training is conducted to enable the classifier to successfully reduce the vocabulary size. Secondly, feature selection enhances classification accuracy by eliminating irrelevant features. The hybrid Gini index and entropy are implemented.

The feature extraction technique with the help of selected parts is done on the part of terms that emerged while preparing, the selected pieces are used in text arrangement segment, A specific target value needs to be identified for a given set of features. You need to extract instances and features from the root word in order to start splitting. As a result, there is a need to evaluate the information of features and to take into the information-richest feature to segregate data. Since informativeness is measured by the information gain, the entropy of the dataset needs to be understood. This is the original training which successfully achieves a reduction in the size of the vocabulary. Second, feature selection improves classification accuracy by discarding irrelevant features.

Gini Index

The Gini Index is utilized to select the optimal feature for partitioning the dataset by reducing impurity at each node. It assists in determining the method of data partitioning at each stage of tree construction.

$$G = 1 - \sum_{i=1}^{C} P_i^2 \qquad (3)$$

Where, in equation (3) G represents the Gini Index (impurity) of a node.

C represents the quantity of potential classes within the dataset. Pi

represents the ratio of samples classified as belonging to class i within the node.

Entropy

Entropy is a notion from information theory that quantifies the degree of uncertainty or disorder inside a dataset. It is frequently employed in decision trees to ascertain the optimal method for partitioning data at each node. It is expressed in equation (4)

Entropy = $\sum_{i=1}^{n} -P(c_i) log_2^c$ (4)

Essential components for constructing a Decision Tree utilizing Information Gain are as follows:

- Initiate all training examples linked to the root node.
- Employ Information gain to determine the attribute for labelling each node.
- Iteratively build every subtree using a specific set of training instances that the tree would classify along that path according to the following:
  - i) If only sarcastic or only non-sarcastic training examples are present, designate that node as “yes” or “no” accordingly.
  - ii) If no attributes are available, assign a label based on the majority vote of the remaining training instances left to that node.
- If no instances are available, label based on the majority vote to the training instances of parent node.

To identify the optimal feature for the root node based on information gain, initially utilize each descriptive feature to partition the dataset according to the values of these features, subsequently calculating the entropy of the dataset. This provides the residual entropy after partitioning the dataset based on the feature values. Subsequently, deduct this value from the initially computed entropy of the dataset to ascertain the extent to which this feature split diminishes the original entropy, hence yielding the information gain of a feature, which is calculated accordingly using equation (5)

$$Information\ Gain(feature) = entropy(Dataset\_ - entropy(feature) \qquad (5)$$

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The feature exhibiting the greatest information gain should serve as the root node for constructing the decision tree. Both Gini and entropy function as metrics of node impurity. A node containing multiple classes is deemed impure, while a node with a singular class is considered pure. Information gain is calculated as the entropy of the parent node subtracted by the sum of the weighted entropies of the child nodes. The weight of a child node is determined by the ratio of the number of samples in that node to the total number of samples across all child nodes.

Pseudo code for feature selection using hybrid approach:

For Each Telugu sentences from the annotated dataset

Do

{

Initiate preprocessing

Start using Gini Index and Entropy-based features as delineated in Equations (3) and (4). Identify the attributes with the highest weights for classification among the optimal k attributes.

}

Train the model using Random Forest and AdaBoost classifier

The sample Decision Tree plots has been depicted from figure to 2 to figure 4 which show Gini values and samples

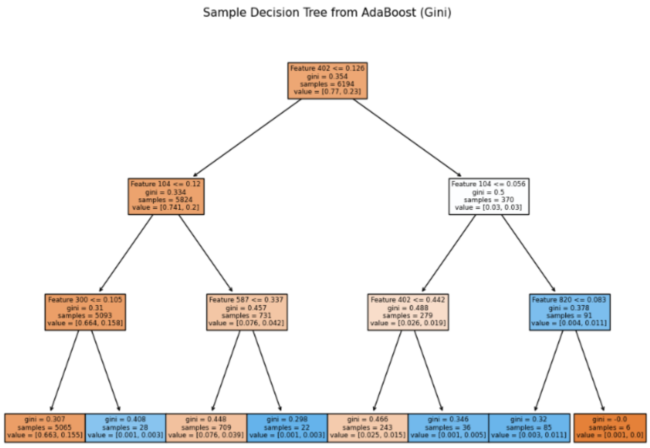

Figure 2: Decision plot Tree from AB classifier

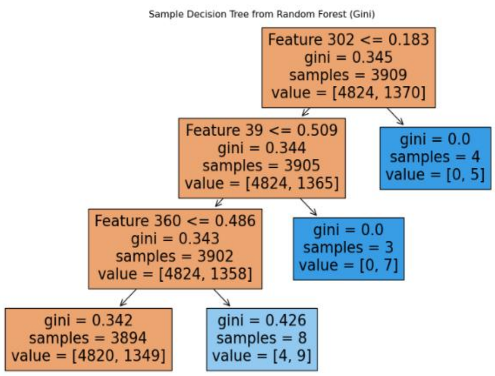

Figure 3: Gini Index values from Random Forest classifier

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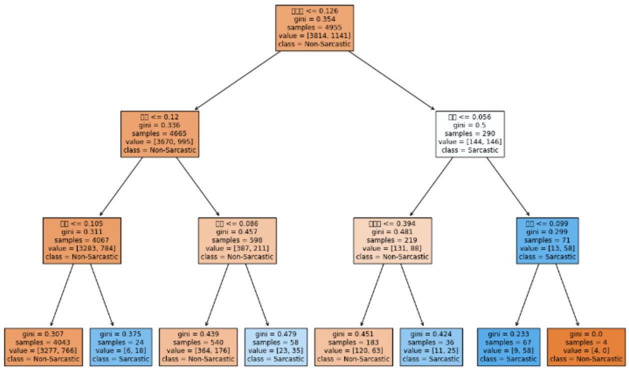

Figure 4: Input plot tree from Decision Tree Classifier

Pseudo code for RF classifier using hybrid feature selection:

Dataset as input and it is trained among multiple decision trees.

1. Preprocess the dataset
2. Split the dataset for training and testing and generate the samples
3. Choose weight factor λ between 0 to 1 to give the influence to gini index and entropy
4. Split the dataset. For each split calculate Gini index and entropy and finally compute hybrid impurity score.

   Hybrid Score=λ×Gini Index+(1−λ)×Entropy

5. Find the best split and repeat the process until met the conditions.
6. Train all the generated trees
7. Majority voting is employed for predictions

Pseudo code for AB classifier using hybrid feature selection:

1. Initialize the weights α as Gini and β as entropy
2. Measure impurity of tree node as Gini as well measure disorder of node as entropy.
3. Weighted combination
   Hybrid Score=α×Gini Index+β×Entropy
4. Select the lowest score for as a feature splitting.
5. Update the weights based on classification error in AdaBoost and Iterate the process with weak learners.

4. EXPERIMENT RESULTS:

Three statistical evaluation indicators were employed to assess the performance of the proposed model: Precision, recall, and F-score presented in equation (6) to (9). These metrics offer a comprehensive assessment of the model's efficacy in identifying sarcasm [17].

The formulas for these metrics are as follows:

Accuracy = $^{Tp\,+\,Tn}/_{Tp\,+\,Tn\,+\,Fp\,+\,Fn}$ (6)

Precision=$T_p/T_p + F_P$ (7)

Recall = $\frac{T_p}{T_{p+F_N}}$ (8)

F-Score = 2 × Precision × Recall / Precision + Recall (9)

Where:

Tp = (True Positive) denotes the quantity of accurately identified sarcastic statements.

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Fp = (False Positive) denotes the quantity of non-sarcastic sentences erroneously categorized as sarcastic. Fn = (False Negative) denotes sarcastic statements that have been erroneously categorized as non-sarcastic.

4.1. Quantitative Analysis:

The three classifiers were trained on the Telugu dataset, which was divided in an 80:20 ratio. The AdaBoost (AB) and Random Forest (RF) algorithms achieved 80% and 76% in the initial trial, respectively among 5 trails shown in Table 2 and figure 5.

Table 2: Accuracy among 5 trials with (80-20) split

Trial	DT	RF	AB
1	0.75	0.76	0.80
2	0.74	0.76	0.79
3	0.74	0.75	0.79
4	0.72	0.75	0.78
5	0.70	0.74	0.78

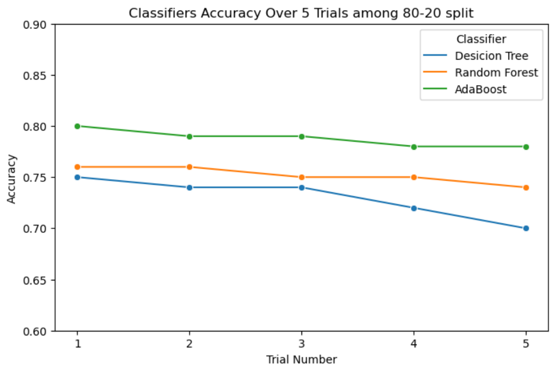

Figure 5: Graphical presentation of accuracy over 5 trails with 80-20 split

Similarly, the dataset is divided into a 60:40 ratio, which is utilized for training and testing among three classifiers: Decision Tree (DT), AB, RF. In five trials, the AdaBoost classifier attained 63% in the second trial, whereas the Random Forest attained 60% in the first trial shown in Table 3. These findings were computed using the equation (6). Based on these observations, the 80:20 split yielded superior accuracy compared to the 60:40 ratio can be shown in figure 5 and 3.

Table 3: Three classifiers accuracy among 5 trials with (60 -40) split

Trial	DT	RF	AB
1	0.56	0.60	0.62
2	0.56	0.58	0.63
3	0.54	0.58	0.59
4	0.52	0.56	0.58
5	0.52	0.54	0.58

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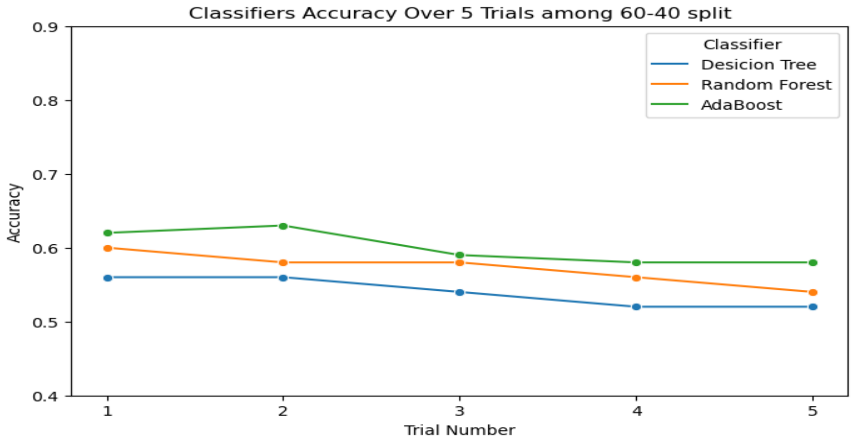

Figure 6: Accuracy among 5 trails with 60-40 split on dataset

The graphical representation of the 60-40 split accuracy is illustrated in Figure 6. There is a progressive decrease among the classifiers.

Table 4: Performance results among multiple Feature Selections

Feature Selection	classifier	Accuracy	Precision	Recall	F-score
Entropy	RF	0.76	0.92	0.53	0.67
Gini index		0.83	0.93	0.69	0.79
Weighted combination of Entropy and Gini Index		0.85	0.94	0.78	0.85
Entropy	AB	0.80	0.91	0.64	0.75
Gini index		0.85	0.94	0.74	0.82
Weighted combination of Entropy and Gini Index		0.89	0.96	0.78	0.86

The AdaBoost classifier demonstrated superior accuracy compared to others inside the respective hybrid feature selection approach. The recall performance of 83% is the highest among the classifiers, indicating the effectiveness in detecting sarcastic statements, particularly the term 'Yes', as illustrated in Table 4. The division of testing and training is conducted in a 20:80 ratio. A stratified split of a total 1300 sentences was conducted for testing, yielding the following accuracy, which is illustrated in Figure 7.

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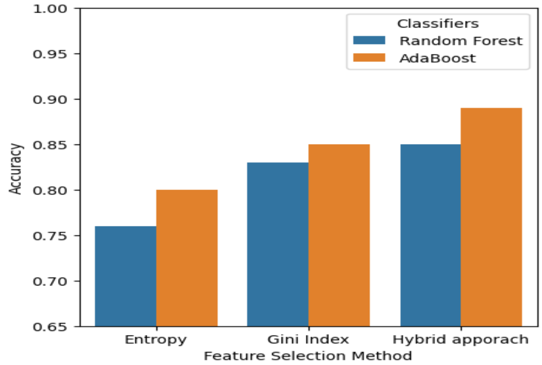

Figure 7: performance comparison analysis among various feature selection

A Receiver Operating Characteristic (ROC) curve is a graphical depiction of a classifier's potential to differentiate across distinct classes. It graphs the True Positive Rate (TPR) versus the False Positive Rate (FPR) across various classification levels. From Figure 8 to 10 illustrates the ROC curves for the hybrid approaches. Findings indicate that an AUC exceeding 0.7 classifies the model as a good classifier. The proposed classifiers achieve the targeted AUC value. The AB classifiers obtained values of 0.89 and 0.87 for individual feature selection methods such as the Gini Index and Entropy. The combination approach achieved 0.91 Show cased in figure 10.

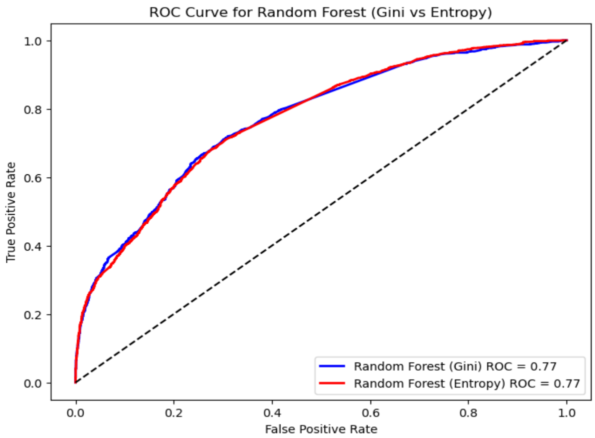

Figure 8: ROC curve for Random Forest algorithm

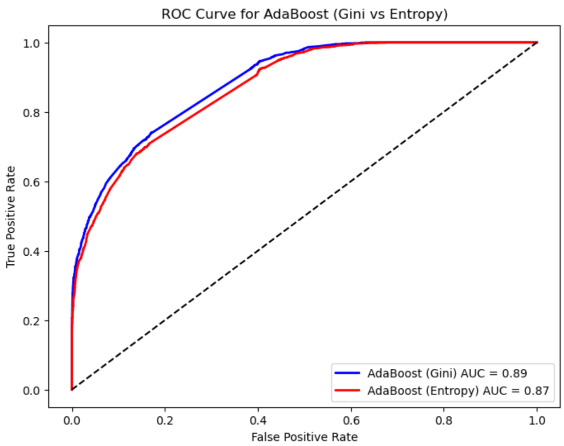

Figure 9: ROC curve for AdaBoost algorithm

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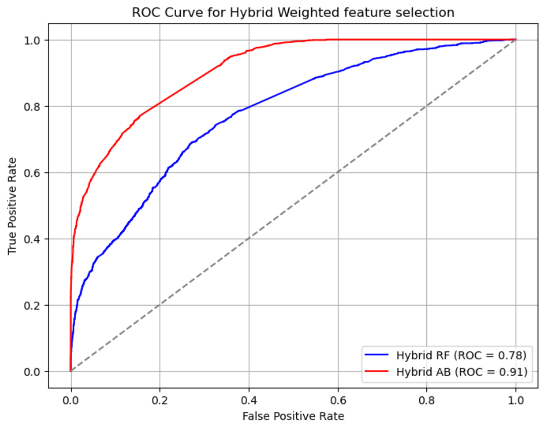

Figure 10: ROC curve for RF and AB classifiers with Hybrid Feature Selection

5. CONCLUSION:

Sarcasm is a sophisticated linguistic device employed by persons to convey the reverse of their literal statements, making it occasionally challenging to figure out [18]. The absence of extensive, annotated datasets constitutes a significant problem and limitation. The proposed classifier attained superior accuracy compared with other feature selection technique. In the future, the dataset can be expanded for enhanced analysis utilizing optimization approaches. Typically, low-resourced languages face challenges due to imbalanced datasets, which may result in diminished precision values. These may be explored more thoroughly with the help of hybrid deep learning architectures.

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