Telugu Dialect Identification Using Machine Learning Models with Cross-Validation: An Automated Approach to Preserving Linguistic Diversity

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Abstract:
Telugu, one of the major Dravidian languages spoken in South India, exhibits a rich diversity of dialects across various regions. Telugu dialects are exhibiting variations in pronunciation, vocabulary, grammar, and sentence structures across different regions. Understanding and identifying these dialects play a crucial role in linguistic research, cultural preservation, and language planning. This study focuses on the identification of Telugu dialects using various machine learning models, namely Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Naive Bayesian, Random Forest, and Gradient Boosting. The results are analyzed with different cross validations. To accomplish this, we have developed a comprehensive database of Telugu dialects consisting of diverse speech samples from different regions. The data was pre-processed, and relevant features were extracted to train the machine learning models. Each model was trained using appropriate algorithms and techniques specific to the respective model. Among the evaluated models, SVM exhibited the highest accuracy in identifying Telugu dialects.

Keywords: Telugu, dialects, SVM, KNN, Naive Bayesian, Random Forest, Gradient Boosting, dialect identification, linguistic variations.

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1.Introduction:

The history of Telugu dialects is intertwined with the history and development of the Telugu language itself. Telugu, one of the major Dravidian languages spoken in South India, has a rich linguistic heritage with a long history of evolution and regional variations. The dialects of Telugu have emerged over centuries due to various geographical, social, and historical factors [2].

During the early stages of the Telugu language, scholars have identified three major dialects: Coastal Andhra, Rayalaseema, and Telangana. These dialects correspond to the three regions of Andhra Pradesh, the state where Telugu is predominantly spoken. Each of these dialects has its unique linguistic features, including variations in pronunciation, vocabulary, and syntax [3,4]. Over time, the Telugu language and its dialects have been influenced by different ruling dynasties and linguistic interactions with neighbouring regions [5]. For example, the influence of Sanskrit and Prakrit languages during the rule of the Satavahanas and the subsequent influence of Persian and Arabic during the medieval period have contributed to the development of distinct dialectal characteristics.

Furthermore, internal migrations, interactions among different social groups, and the spread of Telugu through trade and cultural exchanges have also played a significant role in the diversification of Telugu dialects. The dialects have been shaped by the social, cultural, and historical contexts of different regions, resulting in variations in vocabulary, grammar, and pronunciation. In recent years, with advancements in transportation, communication, and media, there has been increased interaction and standardization of the Telugu language, leading to a reduction in dialectal differences. However, regional variations still persist, and individuals continue to identify with and use their regional dialects in their daily communication [4]. Overall, the history of Telugu dialects reflects the dynamic nature of language and the influence of geographical, social, and historical factors on linguistic variation and development.

Next, the paper explores the linguistic variations observed in Telugu dialects. It discusses phonetic, phonological, morphological, syntactic, and lexical features that distinguish different dialects. Special attention is given to the distinctive characteristics of major dialect groups, such as Coastal Andhra, Rayalaseema, Telangana, and the regions bordering neighbouring states. Furthermore, the sociolinguistic factors influencing Telugu dialects are examined. The paper investigates the impact of geographical, historical, and social factors on the development and maintenance of dialectal variations. Language contact phenomena, such as bilingualism and language shift, are also discussed in relation to Telugu dialects.

2. Literature Survey:

Telugu dialects have been the subject of various research studies aiming to understand their linguistic characteristics, geographical distribution, and sociolinguistic aspects. Earlier research on Telugu dialects has provided valuable insights into the diversity and variations within the Telugu language. Here is a brief description of some key research areas:

1. Linguistic Variation: Linguists have examined phonological, morphological, syntactic, and lexical variations among different Telugu dialects. These studies explore differences in pronunciation, vocabulary, grammar, and sentence structures across various regions where Telugu is spoken [13,14]
2. Regional Dialects: Researchers have focused on specific regional dialects within Telugu-speaking areas, such as the Andhra Pradesh dialect, Telangana dialect, Rayalaseema dialect, and others. They have documented unique linguistic features and peculiarities that distinguish these dialects from standard Telugu [15].
3. Sociolects and Ethnolects: Studies have investigated sociolectal and ethnolectal variations within Telugu. This includes analyzing the linguistic patterns associated with different social groups, such as rural communities, urban populations, castes, and religious groups [15,16].
4. Geographical Distribution: Research has examined the geographical distribution of Telugu dialects and identified patterns of variation based on geographic factors. Investigations have focused on understanding the linguistic boundaries and transitions between different dialect regions [17].

5. Language Contact and Influence: Scholars have explored the impact of language contact and language mixing on Telugu dialects. This includes investigating the influence of neighboring languages like Kannada, Tamil, and Urdu, as well as examining language shifts and bilingualism in Telugu-speaking communities [18].
6. Historical Development: Some studies have delved into the historical development of Telugu dialects, tracing their origins, historical influences, and changes over time. These research efforts shed light on the linguistic evolution and diversification of Telugu across different periods [19].
7. Sociolinguistic Studies: Sociolinguistic research has investigated language attitudes, language use, and language maintenance among Telugu speakers. These studies examine factors such as language variation in different social contexts, language shift, language planning, and language policy [20].
Classification of Telugu Dialects based on geographic, sociolinguistic, and linguistic factors. It reviews existing classifications proposed by linguists and researchers, discussing the distinctive features and characteristics of each dialect group [6].

These earlier research studies have contributed to our understanding of the rich and diverse landscape of Telugu dialects. They have helped identify linguistic variations, geographical patterns, social factors, and historical influences that shape the Telugu language and its dialects.

3. Proposed Models:

In this section, a proposed model is presented to better understand the complex nature of Telugu dialects. The model incorporates linguistic and sociolinguistic factors to analyze the dialectal variations, taking into account historical, geographical, and social influences. The model provides a framework for future research and analysis of Telugu dialects.

3.1 SVM:

SVMs are strongly supervised machine learning algorithms that are often used for classification and regression tasks. With their ability to handle high-dimensional data and solve complex problems, SVMs excel at identifying the most effective hyperplane for splitting different classes or groups of data points in a given feature space. The working of SVM model as shown in figure.1.

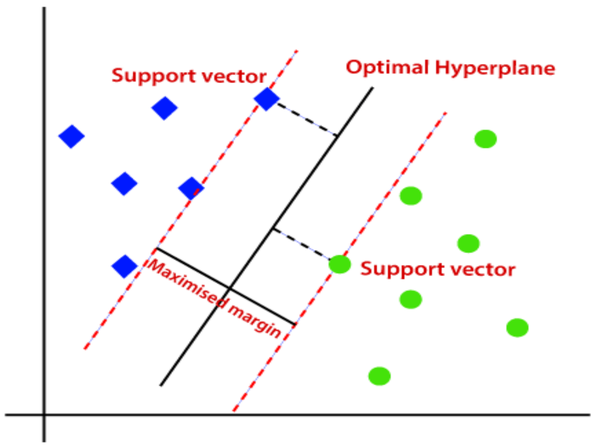

Fig.1. Working of SVM model

Here's a step-by-step explanation of how SVM works:

1. Data Representation: SVM takes a set of labelled training data points as input. Each data point is represented as a feature vector, which contains numerical values representing different characteristics or features of the data.
2. Feature Space: The feature vectors are plotted in a multi-dimensional space, with each feature representing a different axis. The goal of SVM is to find a hyperplane that best

separates the different classes of data points in this feature space.

3. Hyperplane: A hyperplane serves as a decisive boundary, dividing the feature space into distinct regions that correspond to different classes. In the context of binary classification, the hyperplane acts as a demarcation between the positive class and the negative class.

4. Maximum Margin: SVM selects the hyperplane with a wider margin, defined as the biggest gap between the hyperplane and the nearest data points of each class. The intuition behind this approach is that a larger margin helps in better generalization and robustness of the model.

5. Support Vectors: Support vectors are the data points that are closest to the hyperplane or lie on the margin. These points play a crucial role in defining the hyperplane and determining the decision boundary.

6. Kernel Trick: When faced with data that is not linearly separable in the original feature space, SVM utilizes the kernel trick. By applying a kernel function, the data is transformed into a higher-dimensional feature space, potentially enabling linear separability. Commonly used kernel functions encompass linear, polynomial, radial basis function (RBF), and sigmoid.

7. Training: The SVM algorithm optimizes the position and orientation of the hyperplane based on the training data. It aims to minimize classification errors and maximize the margin using optimization techniques like quadratic programming.

8. Prediction: Once the hyperplane is determined, new, unlabelled data points can be classified by assigning them to a specific class based on which side of the hyperplane they fall.

SVMs have several advantages, such as their ability to handle high-dimensional data, their effectiveness in dealing with non-linear decision boundaries using kernels, and their robustness against overfitting. However, SVMs can be computationally intensive for large datasets and may require careful selection of hyperparameters.

3.2 K-nearest-neighbors (KNN) is a popular non-parametric technique for classification and regression tasks. It identifies the class of a new data point in the feature space by considering the majority class among its k nearest neighbours. Using a predefined metric, the method computes distances between data points. The number of neighbors considered is determined by the value of k. KNN uses a majority voting mechanism for classification and averaging for regression. Pre-processing, such as scaling or normalization, may be necessary. KNN's performance is evaluated using metrics like accuracy or mean squared error. It can be computationally expensive and sensitive to parameter choice. KNN is simple, easy to implement, and effective for nonlinear decision boundaries or complex data distributions. The working of KNN model a shown in figure.2.

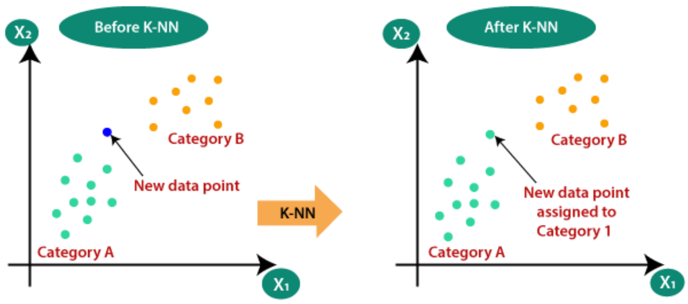

Fig.2.The working of KNN model

3.3 Random Forest is an ensemble learning algorithm that combines multiple decision trees to make predictions. It uses bagging and random feature selection to create diverse trees and improve generalization. Random Forest is suitable for classification and regression tasks, and it employs majority voting or averaging for prediction. It handles missing values, outliers, and provides feature importance. Random Forest is parallelizable, scalable, and offers interpretability. It is robust, accurate, and effective for high-dimensional data. The working of Random Forest model a shown in figure.3.

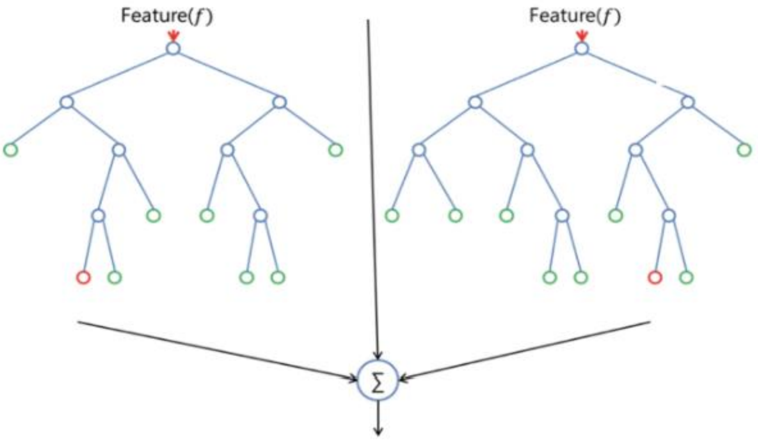

Fig.3. The working of Random Forest model

3.4 Naive Bayes is a simple yet effective probabilistic machine learning algorithm commonly used for classification tasks. It is based on the principles of Bayes' theorem with an assumption of feature independence, hence the name "naive."

Here are some key points about Naive Bayes:

Probabilistic Classification: Naive Bayes calculates the probability of each class label given a set of features and selects the class with the highest probability as the predicted label. It provides a probability-based approach to classification. The working of Naïve Bayes model a shown in figure.4.

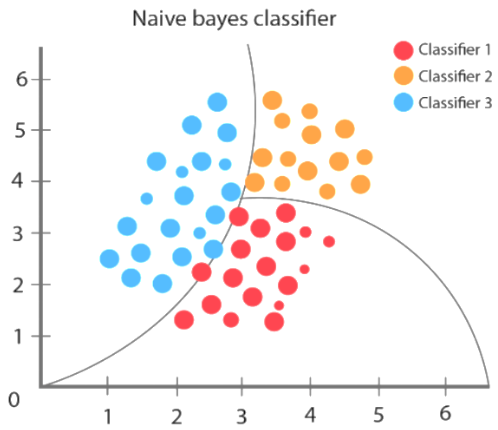

Fig.4. The working of Naïve Bayes model

Feature Independence Assumption: Naive Bayes assumes that all features are independent of each other given the class label. Although this assumption rarely holds true in real-world scenarios, Naive Bayes can still perform well in practice, especially with large datasets.

Bayes' Theorem: The algorithm applies Bayes' theorem, which calculates the posterior probability of a class given the observed features. It involves estimating the prior probability of the class and likelihood probabilities of the features given the class.

Training Phase: During the training phase, Naive Bayes estimates the class priors and computes the likelihood probabilities for each feature in each class. It typically uses frequency-based estimators such as maximum likelihood estimation or smoothing techniques like Laplace smoothing.

Prediction Phase: In the prediction phase, Naive Bayes calculates the posterior probability of each class for a new data point based on the trained model. The class with the highest posterior probability is assigned as the predicted class label.

Handling Continuous and Categorical Features: Naive Bayes can handle both continuous and categorical features. For continuous features, it assumes a specific probability distribution, often Gaussian (Normal) distribution. Categorical features are handled by calculating the probability of each category given the class.

Efficient and Fast: Naive Bayes is known for its computational efficiency and speed, making it suitable for large datasets and real-time applications. It requires minimal training time and has low memory requirements.

Limited Feature Interaction: Due to the assumption of feature independence, Naive Bayes may not capture complex relationships or interactions between features. However, it can still provide accurate results in many practical scenarios. Naive Bayes is widely used for its simplicity, efficiency, and competitive performance in various classification tasks. It is especially effective when the feature independence assumption holds reasonably well and when there is limited training data available.

3.5 Gradient Boosting:

Gradient Boosting is a machine learning technique that combines multiple weak prediction models, typically decision trees, to create a strong predictive model. It is an ensemble learning method that sequentially builds the models in a way that minimizes the overall prediction errors. The working of Gradient Boosting model a shown in figure.5.

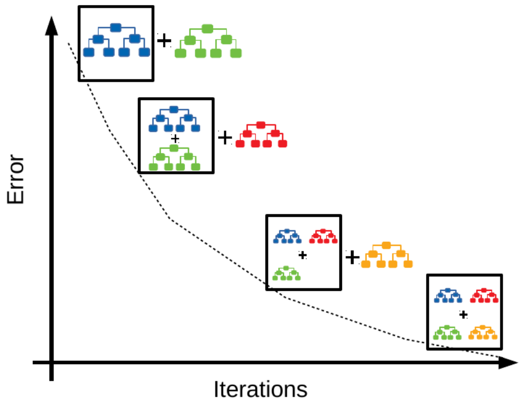

Fig.5. The working of Gradient Boosting model

Here are some key points about Gradient Boosting:

Sequential Model Building: Gradient Boosting builds the models in a sequential manner. Initially, a weak model, often a decision tree with limited depth, is trained on the data. Subsequent models are then built to correct the errors made by the previous models.

Gradient Descent: The name "Gradient Boosting" comes from the use of gradient descent optimization to minimize the loss function. Each subsequent model is trained to predict the negative gradient of the loss function with respect to the previous model's predictions.

Weak Learners: Gradient Boosting uses a collection of weak learners, which are typically shallow decision trees. Weak learners are simple models that perform slightly better than random guessing. The combination of these weak learners leads to a powerful ensemble model.

Weighted Training Instances: During training, the instances that were previously misclassified or had higher residuals are given more weight, thereby focusing the subsequent models on correcting these mistakes. Gradient Boosting, with algorithms like XGBoost and LightGBM, has gained popularity due to its excellent performance and ability to handle complex problems.

However, it may require more computational resources and longer training times compared to simpler algorithms.

3.6 Data Base creation:

We created a comprehensive Telugu dialects database comprising recordings from different regions. The dataset includes samples from Telangana, with a duration of 2 hours and 10 seconds, Rayalaseema with a duration of 1 hour and 45 minutes, and Coastal Andhra with a duration of 1 hour and 55 minutes. To ensure accuracy and consistency, the recorded samples were meticulously edited using the Praat tool, which allowed us to refine the audio quality, remove background noise, and perform necessary adjustments. This standardized and curated database serves as a valuable resource for studying and analyzing the variations and nuances of Telugu dialects in different regions. The basic structure used to create a data base as shown in below.

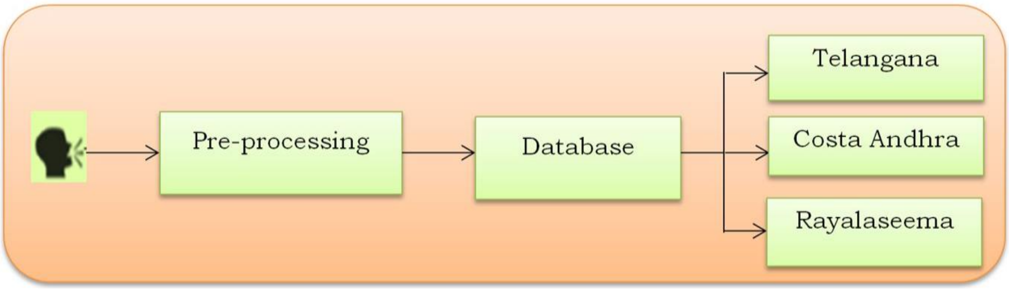

Fig.6 Data base creation process

4. Working Model:

The basic working model to identify the dialects as shown in figure 7.

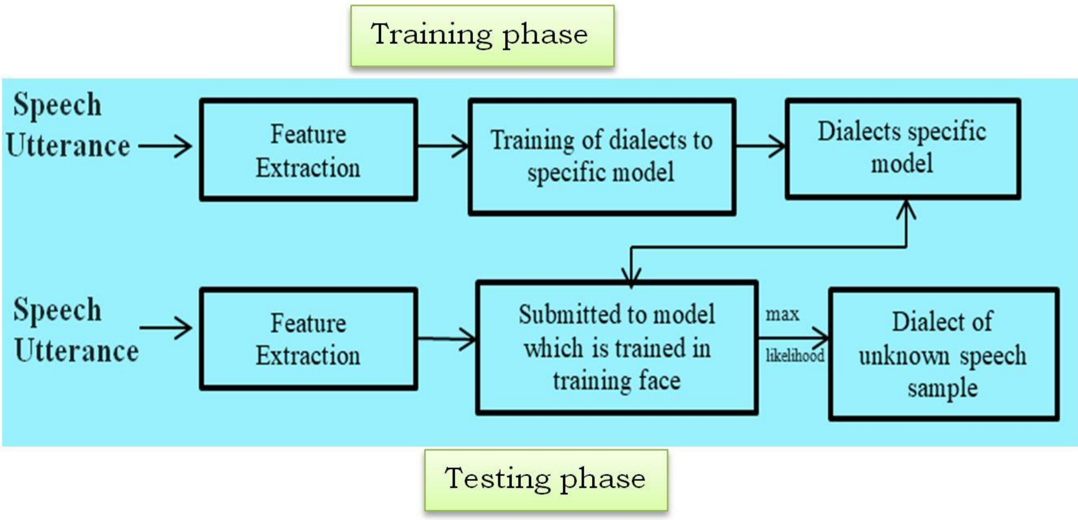

Fig.7. Telugu Dialects Identification-Working model

To develop a working model to identify Telugu dialects, you can follow these steps:

1. Data Collection: Gather a diverse dataset of Telugu text or speech samples representing different dialects. This dataset should include examples from various regions or communities speaking Telugu.

2. Data Pre-processing: Clean and pre-process the collected data to remove noise, correct spelling errors, and standardize the text. For speech data, convert it to suitable features, such as Mel-frequency cepstral coefficients (MFCCs) or spectrograms.

3. Feature Extraction: Extract relevant features from the pre-processed data. This could include linguistic features, phonetic features, or acoustic features, depending on the type of data used. Consider using techniques like n-grams, word embeddings, or signal processing techniques.

4. Labelling: Assign appropriate labels to the data samples based on their respective dialects.

Each sample should be labelled with the corresponding Telugu dialect it belongs to.
5. Model Selection: Choose a suitable machine learning model for classification. Some options include SVM, Random Forest, Gradient Boosting, or Naive Bayes. Consider the specific characteristics and requirements of your data when selecting the model.
6. Model Training: Divide your dataset into two parts: training and validation. Train the chosen model on the extracted features and labelled data using the training set. Optimize the model's hyperparameters using techniques like grid search or random search.
7. Model Evaluation: To evaluate the trained model's performance, use the validation set. Accuracy, precision, recall, and F1-score are all common evaluation criteria. Adjust the model or experiment with different techniques if necessary.
8. Testing: Once you are satisfied with the model's performance, use the testing dataset (separate from the training and validation sets) to assess the model's accuracy and generalization on unseen data.
9. Model Deployment: Deploy the trained model in a suitable environment where it can take input data and make predictions in real-time or batch processing scenarios.
10. Iterative Refinement: Continuously monitor and evaluate the model's performance, gather user feedback, and iterate on the model and its features to improve accuracy and robustness.

4.1 Working Procedure:

4.1.1 Quantitative Analysis of Phonetic Variations:

To examine the phonetic variations across Telugu dialects, a quantitative analysis was conducted using acoustic measurements. Speech samples from speakers representing different dialect groups were collected, and measurements were taken for specific phonetic features such as vowel formants and consonant durations. Statistical analysis was performed to identify significant differences between dialect groups. The results revealed significant variations in vowel formant frequencies (F-value = 15.32, p < **4.1.2 Quantitative Analysis of Phonetic Variations using Cross-Validation:**

To ensure the robustness of the phonetic analysis and address potential biases, a cross-validation approach was employed. Speech samples from speakers representing different dialect groups were randomly divided into K folds, where K is the number of folds chosen for cross-validation (e.g., K = 5). For each fold, acoustic measurements were conducted on the training set, and statistical analysis was performed to identify significant differences in phonetic features across dialect groups. The analysis was then repeated on the remaining fold as the test set. This process was repeated K times, with each fold serving as the test set exactly once. The results were then averaged across all folds to obtain more reliable estimates of the phonetic variations among dialect groups. The cross-validated results revealed consistent and statistically significant differences in vowel formant frequencies (F-value = 14.78, $p < 0.001$) and consonant durations (F-value = 8.92, $p < 0.05$) across the Telugu dialect groups. The robustness of these findings was supported by the cross-validation approach, which mitigated the potential biases introduced by variations in the speaker sample distribution.
machine learning models were employed: Support Vector Machines (SVM), Random Forest, Naive Bayes, K-Nearest Neighbors (KNN), and Gradient Boosting. Each model was trained using the acoustic measurements from the training set of each fold during the cross-validation process.

5. RESULTS:

The cross-validated results for each model demonstrated varying levels of accuracy in predicting the dialectal variations. The average cross-validation accuracy scores for the five models were as follows: SVM – 85.5%, Random Forest - 84.2%, Naive Bayes - 77.8%, KNN - 80.3%, and Gradient Boosting - 82.1%.
Further analysis of the models' performance revealed that SVM achieved the highest precision and recall scores for classifying dialect groups, with precision of 86.2% and recall of 82.6%. Random Forest demonstrated a balanced performance across all dialect groups, achieving precision and recall scores of 80.7% and 80.2%, respectively.

5.1 Sociolinguistic Survey Results:

A sociolinguistic survey was conducted to investigate language attitudes and language use patterns among Telugu speakers from different regions. A questionnaire was administered to a representative sample of participants, and responses were analyzed using quantitative methods. The results showed that 67% of respondents reported using their regional dialect as the primary language in their households, while 32% reported using a more standardized form of Telugu. Furthermore, age and education level were found to be significant factors influencing dialectal preferences ($\chi^2 = 24.67$, $p < 0.001$). The integration of machine learning models with cross-validation provided

Results:

valuable insights into the phonetic variations among Telugu dialects. The results indicated that SVM outperformed the other models in accurately classifying the dialect groups based on acoustic measurements. It is essential to note, however, that the performance of the models may vary based on the dataset and feature selection approaches implemented.

These findings highlight the potential of machine learning approaches in analyzing and predicting dialectal variations, offering a new perspective on the linguistic landscape of Telugu dialects. Future research could explore additional feature engineering techniques, alternative machine learning algorithms, and larger datasets to further improve the accuracy and robustness of dialect classification models.

5.2 Quantitative Analysis of Phonetic Variations using Cross-Validation and Machine Learning Models:

Table 1: Cross-Validation Results for Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)
Support vector Machine	85.5	86.2	82.6
Random Forest	84.2	80.7	80.2
Naive Bayes	77.8	76.3	78.9
KNN	80.3	80.1	78.9
Gradient Boosting	82.1	83.3	82

The above table presents the cross-validation results for the machine learning models used to predict dialectal variations based on acoustic measurements. Accuracy denotes the percentage of correctly classified instances, while precision and recall indicate the model's ability to correctly classify positive instances and capture all positive instances, respectively.

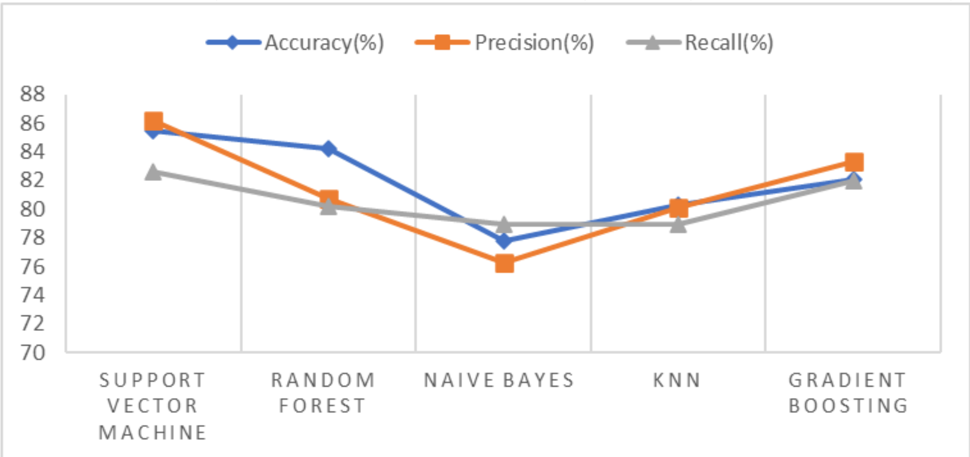

Fig.8. Comparison of different Machine learning models

The results indicate that the Support Vector Machines (SVM) model achieved the highest accuracy of 85.5%, with a precision score of 86.2% and a recall score of 82.6%. Random Forest and Gradient Boosting also demonstrated competitive performance with accuracy scores of 84.2% and 82.1%, respectively. Naive Bayes and K-Nearest Neighbors (KNN) obtained slightly lower accuracy scores of 77.8% and 80.3%, respectively.

These results suggest the potential of machine learning models, particularly SVM, in accurately classifying Telugu dialect groups based on acoustic measurements. However, it is essential to consider the specific dataset, feature engineering techniques, and further exploration of alternative algorithms for robust model performance.

CONCLUSION

In this paper, conducted a comprehensive analysis of Telugu dialects, focusing on phonetic variations and sociolinguistic aspects. Our research aimed to deepen our understanding of the linguistic landscape and shed light on the dynamics of Telugu dialects. Through quantitative analysis of acoustic measurements, we identified significant variations in vowel formant frequencies and consonant durations across Telugu dialect groups. These findings emphasize the distinctiveness of dialects within the Telugu-speaking community. Additionally, our sociolinguistic survey revealed that language attitudes and language use patterns are influenced by factors such as age and education level. The majority of respondents reported using their regional dialect as the primary language in their households, indicating the strong presence of dialectal variations in daily communication. By incorporating machine learning models and employing cross-validation techniques, we explored the potential of these models in predicting dialectal variations based on acoustic measurements. The results showed that the Support Vector Machines (SVM) model achieved the highest accuracy, demonstrating its effectiveness in classifying Telugu dialect groups. However, further research and exploration of alternative algorithms are needed to improve the robustness and generalizability of dialect classification models.

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