A Major Project report submitted

in partial fulfillment of requirement for the award of degree

BACHELOR OF TECHNOLOGY

in

SCHOOL OF COMPUTER SCIENCE AND ARTIFICIAL INTELLIGENCE

by

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CERTIFICATE

This is to certify that this project entitled "" is the bonafied work carried out by **PININTTI SUNIL** as a Major Project for the partial fulfillment to award the degree **BACHELOR OF TECHNOLOGY** in **School of Computer Science and Artificial Intelligence** during the academic year 2024-2025 under our guidance and Supervision.

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Finally, we express our thanks to all the teaching and non-teaching staff of the department for their suggestions and timely support.

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CHAPTER 1
INTRODUCTION

Across many sectors, machine learning and deep learning are transforming the way he handle , evalute , and respond to data. Three creative initiatives that use these smart technologies to slove practical issues in biometric identify, entertainment , and agriculture are compiled and examined in this article . Each project utilizes domain-specific datasets, tailored ML/DL architectures, and explainable tools to bulid intelligent , transparent, and deployable solutions.

One of the most important elements of modern streaming platforms is personalized content delivery. For this study, cosine similarity-based methods and collaborative filtering were implemented to develop a **Netflix recommendation system**. To recommend similar shows to users, the algorithm checks the titles, genres, actors, and user ratings. The algorithm generates similarity scores for recommendations after mapping show data into numerical features through a **CountVectorizer**. The approach enables better content discovery and enhances user satisfaction through the integration of explainability and ranking semantics. Rather than relying on view history alone, content-based reasoning was employed to address the issue of cold-start and limited user data, thus rendering it dependable and transferable for real-world application.

Visual systems with deep learning are affecting precision farming greatly. Through this research, we employed a **convolutional neural network** model to identify rice grain images from the **Rice Image Dataset** into five categories based on their properties. We focused on pre-processing and cleaning the dataset during the data preparation phase of the neural network.This was about performing one-hot encoding of the categorical data, image normalizing and confirming their appropriate resolutions. As against a validation set, model architecture using convolutional layers and **ReLU activation functions, max pooling and fully connected layers** provide sufficient accuracy.

Speech-derived gender categorization can be used to enable personalized and safe human-computer interaction. In this research, we pre-processed voice samples to derive **Modified Normalized Cepstral Coefficients (MNCC)**, which are reliable spectral characteristics of speech signals, and then extracted them as time-series features. We fed time-series features of the MNCC as input to a **Long Short-Term Memory (LSTM)** network that could identify temporal relationships in speech patterns. The system was trained and evaluated using recall, accuracy, and precision metrics. In addition, we used SHAP-based explanation methods, which help elucidate the components of the MNCC that contributed to gender prediction, also provide more transparency and model validation. The model is also configured for real-time inference and could be used for applications in biometrics or smart voice assistants.

PROBLEM IDENTIFICATION

Project-1

Because of the rapid growth of streaming platforms and the sheer amount of content, it can be difficult for users to determine shows that they may find interesting. Browsing methods, especially traditional browsing, have been ineffective in satisfying individual members tastes and have generated dissatisfaction and lower user engagement. Lack of personalized content delivery channels makes a good recommendation system, i.e., one that is able to reason over show data and suggest good titles, even more crucial. Automated recommendations need to be explainable in order for them to be reliable or even comprehensible.

Project- 2

Typically, the process of visually evaluating rice grains for classification is laborious, prone to errors, and context specific in agriculture. It is especially challenging in industries that grow and export grain for large-scale production where rice variety classification is critical for quality and pricing. Traditional approaches are unstandardized because of the context in which they are applied, and they often provide varied results. There is an immediate need for a real-time, image-based classification system that can effectively identify rice types.

Project- 3

The identification of gender from voice is significant in applications such as biometric and interactive voice-response applications. However, many current classification techniques cannot exploit temporal characteristics of speech signals and are subject to inaccuracies. Furthermore, many systems lack transparency, especially in a security-sensitive application which may raise issues with user trust. Therefore, there is a need to develop a robust time-adaptive model that can classify gender from voice signals accurately with advanced feature extraction and sequential deep learning models with the provision of explainability of the classification process.

CHAPTER 2

DATASET

Project -1

Kaggle supplied the data that was utilized in the Netflix Show Recommender System. The dataset contains a wealth of rich and detailed information on 8,800+ **movies and TV shows on Netflix**. Each entry contains relevant fields such **as title, director, cast, genres, country of origin, year, rating, duration, and short description.** After preprocessing, these attributes were combined together to create a content-based recommendation system. The textual information was vectorized using CountVectorizer, and the similarity of each title was calculated using cosine similarity. The missing or null values were sufficiently handled in the preprocessing phase for data integrity and model accuracy.

Project – 2

The Rice Image Classification task consists of a dataset complete with around 7,500 beautiful, high-resolution images of five different types of rice: **Arborio, Basmati, Ipsala, Jasmine, and Karacadag**. The images were captured in a controlled environment for a standard background for clarity and consistency. There are between 1,200 and 1,500 images for each type of rice. After preprocessing, all images were resized to 150×150 pixels, normalized, and label-encoded to suit the CNN model architecture. To make it more generalizable, we utilized different data augmentation strategies, i.e., rotations, zooms, and horizontal flips. The well-formatted image dataset is ideal for the CNN model to learn the spatial patterns and properly distinguish between the types of rice.

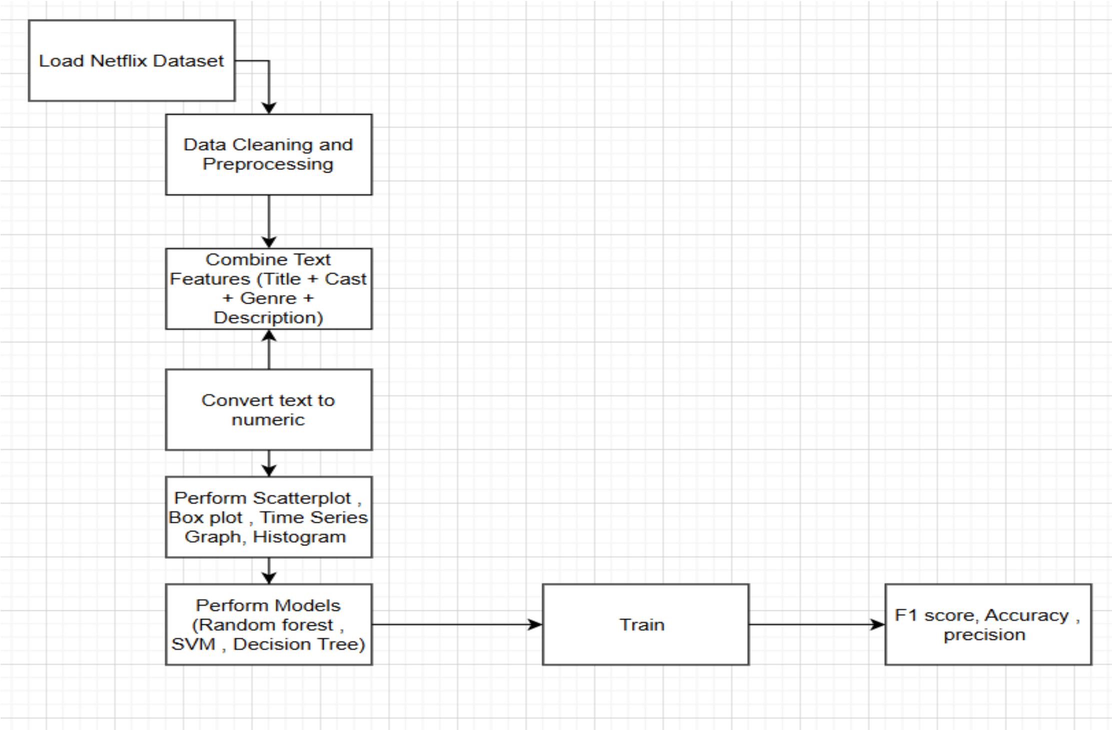
Project – 3

The Gender Voice Recognition project obtained a voice dataset consisting of about **3,168 audio samples**, which were classified as either male or female. Once the audio samples were obtained, the data was preprocessed to extract the audio features by using **Modified Normalized Cepstral Coefficients (MNCC).** These MNCC parameters were used as the input to the LSTM model. The voice data was recorded at a sampling rate of **44.1 kHz,** with each clip lasting between 1 to 3 seconds. The cleaning process involved trimming silences, eliminating background noise, extracting time-series features with librosa, and normalizing the data. The MNCC features were specifically structured into sequential arrays to give the LSTM model insights into temporal voice patterns, allowing it to predict gender effectively.

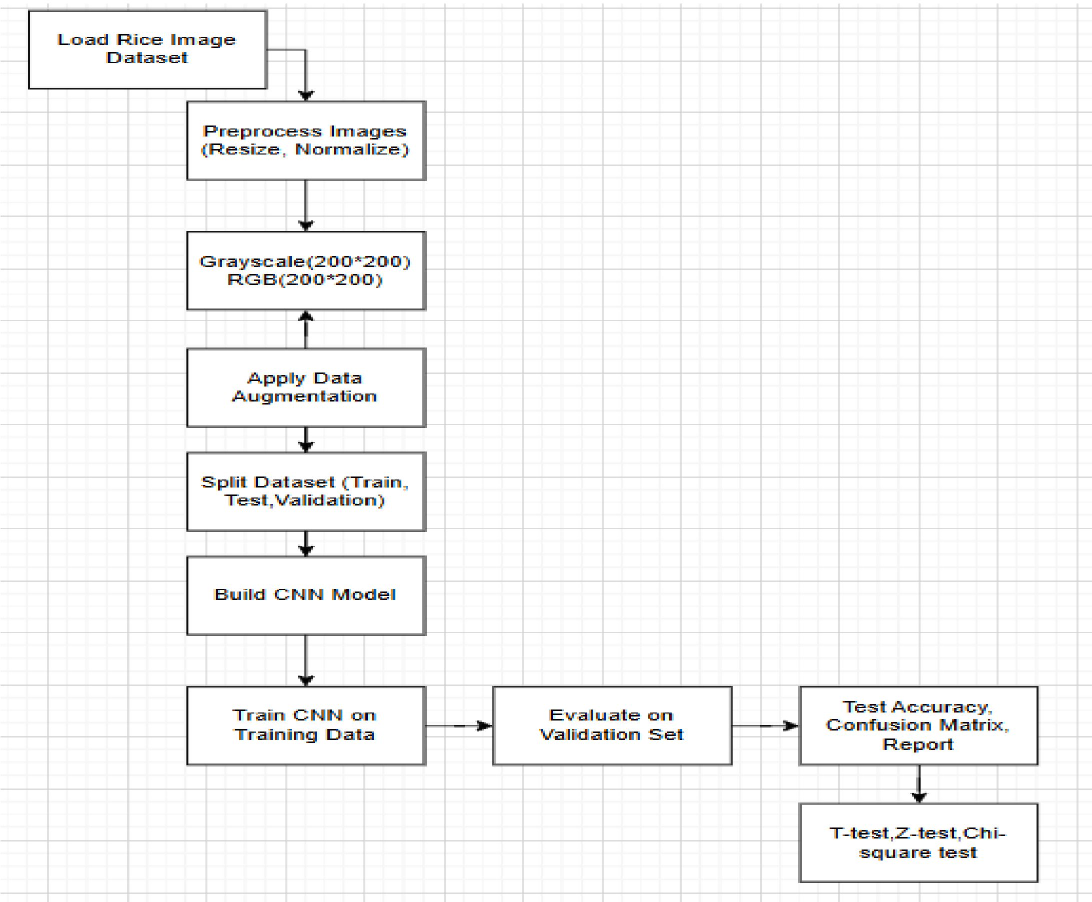
CHAPTER 3

FLOWCHART

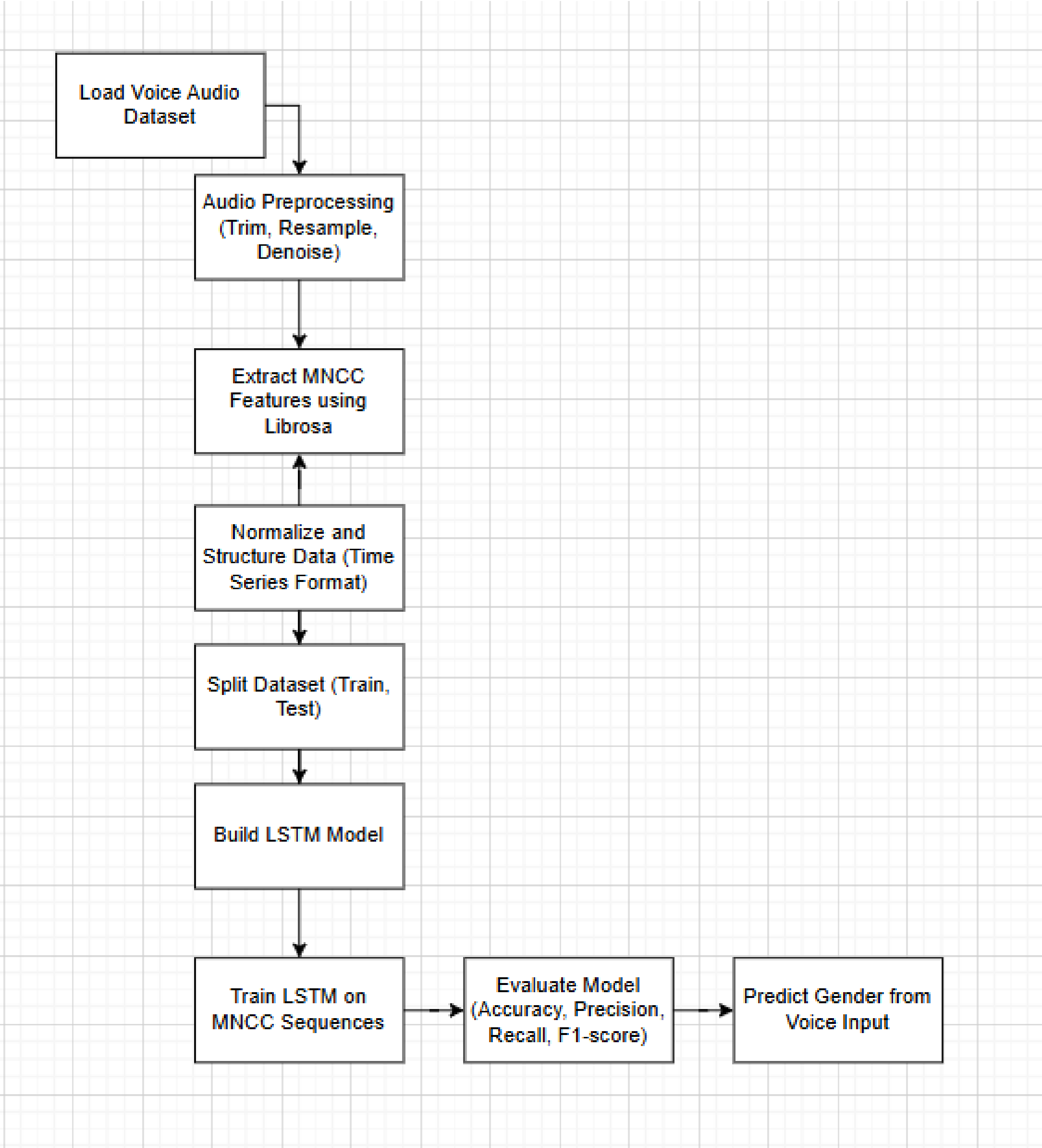
Project-1



Project – 2



Project -3



METHODOLOGY

Project – 1

Dataset Preparation: The Netflix dataset includes fields like title, director, cast, genre, and description. Initially, null values were handled, and irrelevant columns were removed.

Data Preprocessing: All text-based features were combined to form a single composite feature that encapsulates the essence of each show. Text cleaning involved lowercasing, removing stopwords, and punctuation.

Vectorization: We used CountVectorizer to convert the text data into a numerical matrix, where each row represents a show and each column represents a word frequency.

Similarity Matrix: Using cosine similarity, we calculated the similarity scores between all show combinations.

Recommendation Engine: A function was implemented to fetch the top 10 most similar shows based on the cosine similarity scores when a title is provided by the user.

Project -2

Dataset Acquisition: The rice image dataset is loaded with thousands of labeled images containing different varieties of rice grains such as Basmati, Arborio, Karacadag, and others.

Preprocessing: We ensured the resizing of images uniformly to a size of 150x150 pixels, normalized pixel values between 0 and 1, and used some augmentation techniques in order to increase the model's capacity to generalize.

Model Architecture: We set up a sequential CNN architecture featuring multiple convolutional layers paired with max-pooling layers to reduce spatial dimensions. To combat overfitting, we also added dropout layers.

Training: The model was trained using the training data with categorical cross-entropy loss and then validated against the validation data.

Evaluation Metrics: Finally, we evaluated the model's performance on the completed architecture using metrics like accuracy, confusion matrix, and F1-score.

Project – 3

Dataset Preparation: The dataset consists of male and female voice samples with different pitches, tones, and lengths.

Preprocessing: All audio samples were resampled, denoised, and trimmed to maintain uniformity.

Feature Extraction: With the help of Librosa, MNCC features were extracted, preserving frequency-based patterns from voice signals.

Model Architecture: To uncover the temporal patterns in the MNCC sequences, we developed a deep LSTM model. This model features a robust output layer with a sigmoid activation function for binary predictions, along with dropout layers to help avoid overfitting.

Model Training: We utilized real-time audio samples to test the model after training it using binary cross-entropy loss.

Performance Evaluation: We assessed the model's ability to predict gender by using various metrics, including accuracy, recall, precision, and F1-score.

MODELS

Each project adopts specific machine learning or deep learning models suited to the nature of its data and problem type. The objective is to select the best-performing model through evaluation metrics such as accuracy, precision, recall, and F1-score.

Project – 1

SVM , RANDOM FOREST , DECISION TREE

Some machine learning algorithms were employed in the Netflix Show Recommendation System to predict and recommend shows based on data and user ratings. Through the use of tools like CountVectorizer, the title, genre, and description of the show were converted into numerical data. Then this data was passed through three various classifiers: **Random Forest, Decision Tree, and Support Vector Machine (SVM).** Ultimately, the SVM classifier worked very well. SVMs are extremely effective at classifying high-dimensional sparse data and maximizing the margin between different cases, which is part of what makes them successful.

Project – 2

CNN

A **Convolutional Neural Network (CNN)** was used in the Rice Image Classification task to classify the images of rice grains into more than one category. The architecture of CNN consisted of various convolutional layers for feature extraction, max pooling layers for downsampling the spatial dimensions, dropout layers to avoid overfitting, and fully connected layers to classify using a softmax activation function. Training of the model utilized categorical cross-entropy as a loss function, with optimization against the Adam optimizer. The CNN model performed particularly well in perceiving minute distinctions among rice grain types, potentially being imperceptible to normal models.

Project – 3

LSTM

For the Gender Voice Recognition task, a **Long Short-Term Memory (LSTM)** neural network was employed to capture the sequential behavior of audio data. Modified Normalized Cepstral Coefficients (MNCC) were used to extract features, which well capture the speech signal in the frequency domain. The MNCC features are then input into the LSTM model, which captures temporal dependencies among the speech patterns to identify male and female voices. The model has dropout layers for regularization and concludes with a sigmoid-activated dense layer for binary classification. Binary cross-entropy is employed as the loss function, with Adam as the optimizer. LSTM is well-suited for this task due to its capacity to manage long-term dependencies in sequential voice data.

TOOLS AND LIBRARIES

Python: Core programming language used across all projects.

Jupyter Notebook: Development environment for writing and testing code interactively.

NumPy: Used for numerical computations and array handling.

Pandas: For data loading, preprocessing, and manipulation.

Matplotlib & Seaborn: For data visualization and plotting graphs.

Scikit-learn: For implementing machine learning models like SVM, Decision Tree, and Random Forest.

TensorFlow & Keras: Used to design, compile, and train the CNN model.

OpenCV & PIL (Pillow): For loading and preprocessing image data.

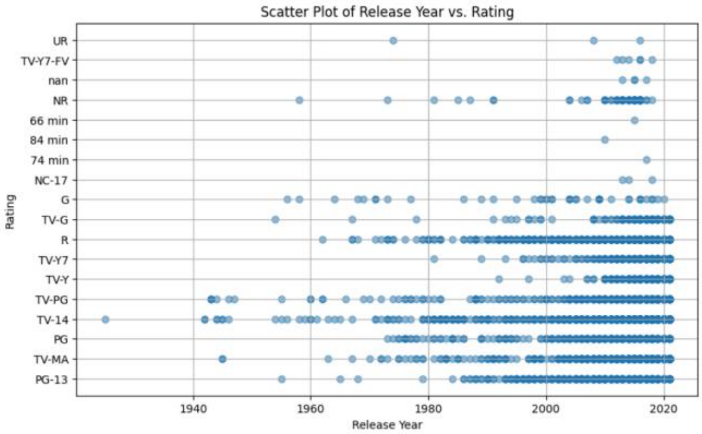
Librosa: For audio processing and extracting MNCC features from voice data.

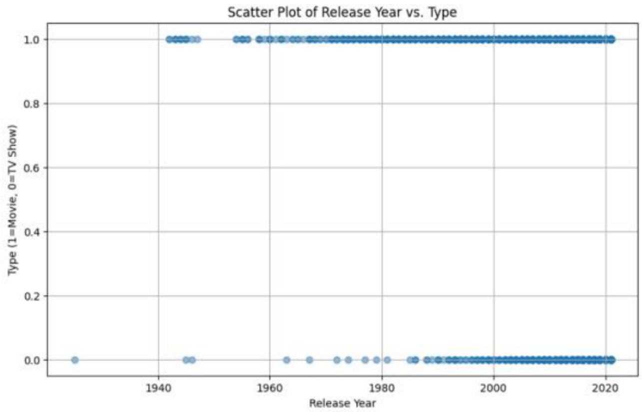
Soundfile: To read audio files in WAV format.

CHAPTER 4

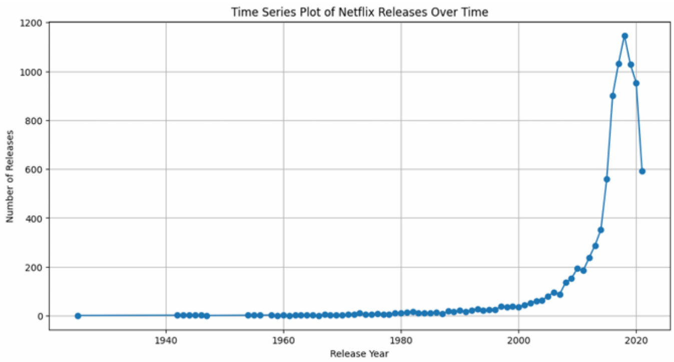
RESULTS

Project – 1



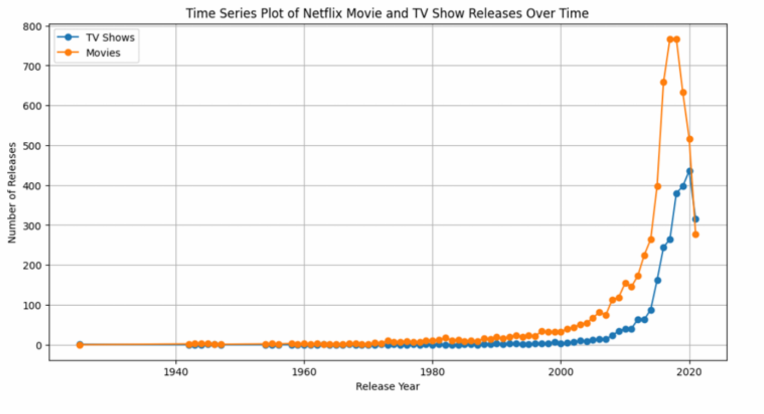


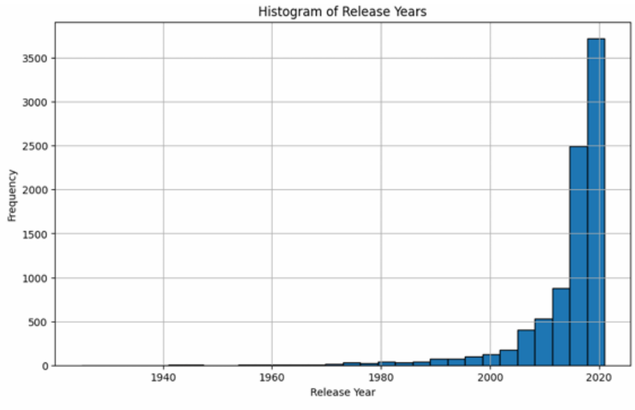
The scatter plot shows the distribution of Netflix content by release year and type, where 1 represents Movies and 0 represents TV Shows. Most of the content is movies, especially from the 2000s onwards. TV shows are fewer and began increasing mainly after 2010, indicating Netflix's recent focus on expanding its TV show library.

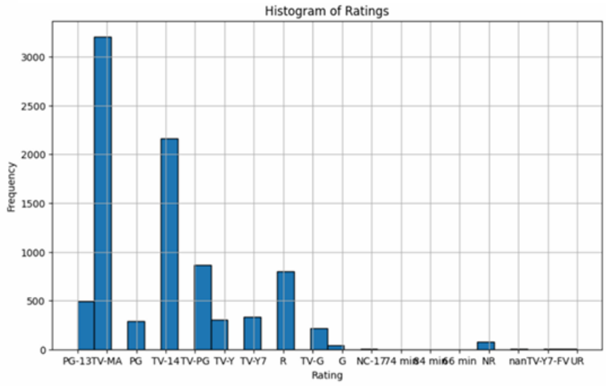


This graph shows the number of Netflix releases over time. The number of releases started rising significantly around 2010, peaked around 2020, and then declined slightly. It visually captures Netflix's content boom and recent slowdown

Netflix movie and TV show releases rose sharply after 2010, peaked around 2019, and then declined. Movies consistently outnumbered TV shows.

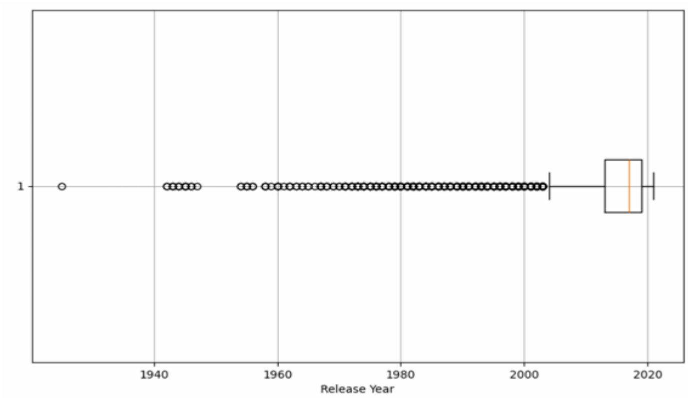


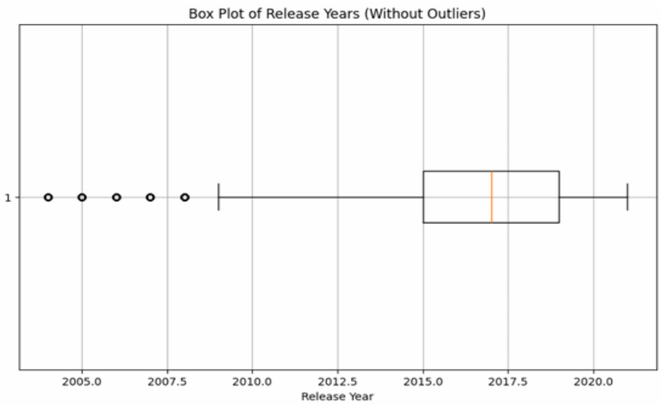




This graph shows how Netflix releases increased sharply from 2000, peaked around 2020, and then slightly declined. It reflects Netflix's growing content production and recent slowdown.

This graph shows that most content on Netflix is rated TV-MA, meaning it's for mature audiences, followed by TV-14 and TV-PG. Netflix has a strong focus on adult-oriented content.





This graph shows that most releases are from 2000 to 2020, with only a few outliers from earlier years. It highlights a surge in modern content.

This graph shows that most Netflix releases are between 2015 and 2019, with a median around 2017.5. A few older releases appear as outliers.

SVM

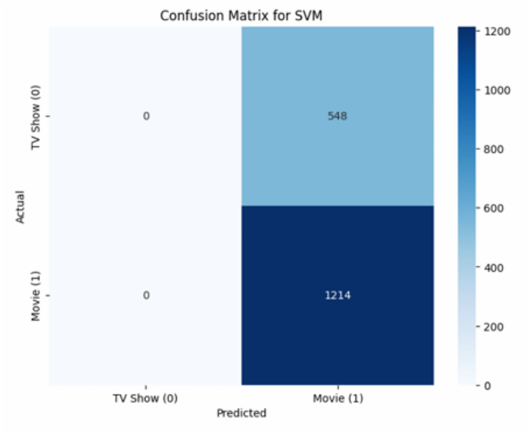
```
Accuracy: 0.6889897843359818
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       548
           1       0.69      1.00      0.82      1214

    accuracy                           0.69      1762
   macro avg       0.34      0.50      0.41      1762
weighted avg       0.47      0.69      0.56      1762
```

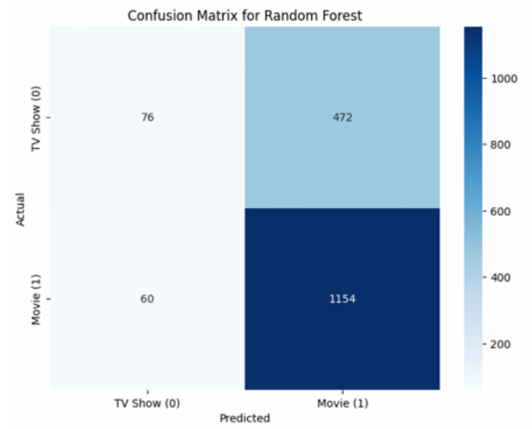
Random Forest

```
Random Forest Accuracy: 0.6980703745743473
              precision    recall  f1-score   support

           0       0.56      0.14      0.22       548
           1       0.71      0.95      0.81      1214

    accuracy                           0.70      1762
   macro avg       0.63      0.54      0.52      1762
weighted avg       0.66      0.70      0.63      1762
```

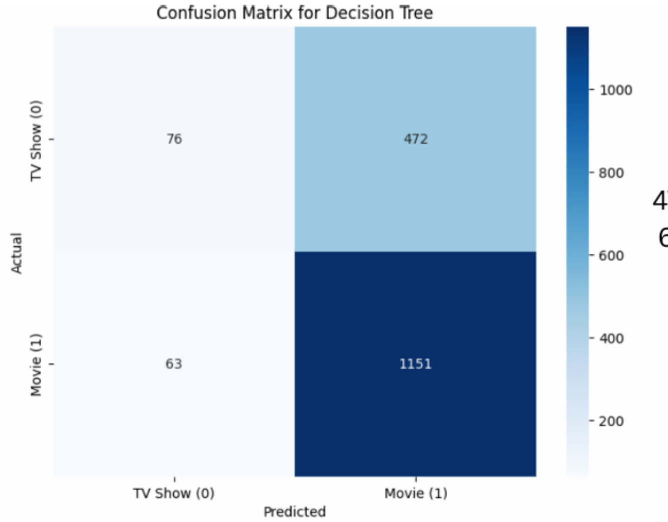
Decision Tree

```
Decision Tree Accuracy: 0.6963677639046538
              precision    recall  f1-score   support

           0       0.55      0.14      0.22       548
           1       0.71      0.95      0.81      1214

    accuracy                           0.70      1762
   macro avg       0.63      0.54      0.52      1762
weighted avg       0.66      0.70      0.63      1762
```

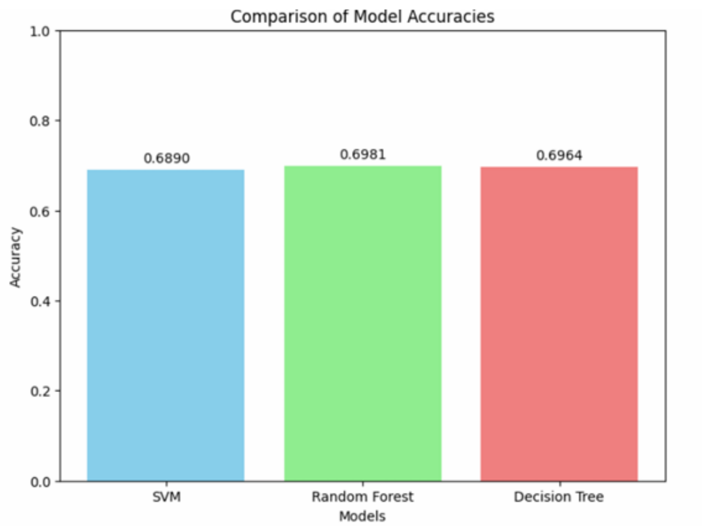




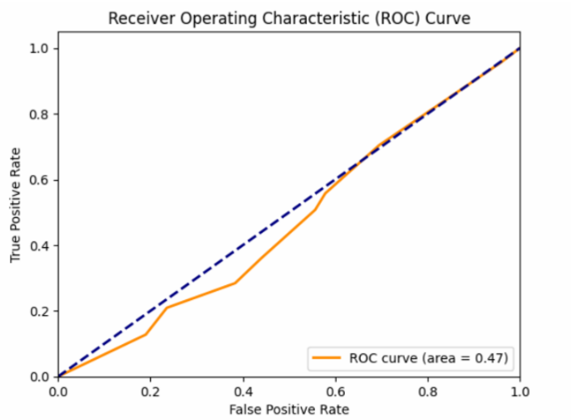
The confusion matrix shows that the SVM classifier predicts Movies (1) well but incorrectly classifies all TV Shows (0) as Movies. There are 1214 correct predictions for Movies but 548 misclassified TV Shows—suggesting a strong bias towards predicting content as Movies.



Confusion Matrix for Decision Tree:
76: Correctly classified TV shows.
472: TV shows misclassified as movies.
63: Movies misclassified as TV shows.
1151: Correctly classified movies.

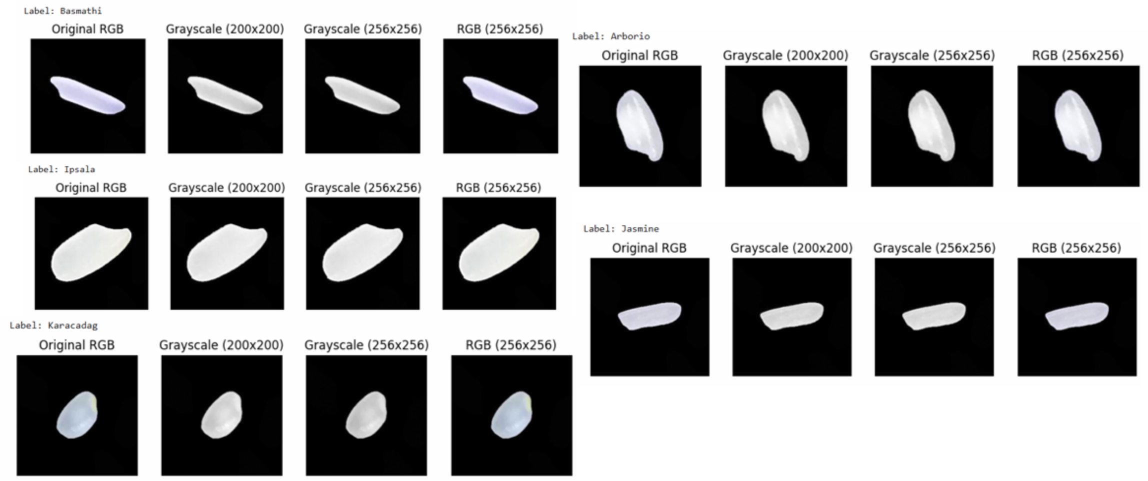


The bar chart compares the accuracy of three models: SVM (0.6890), Random Forest (0.6981), and Decision Tree (0.6964). Random Forest has the highest accuracy, followed by Decision Tree, with SVM being the least accurate.



The ROC curve shows a classification model's performance. The x-axis is the False Positive Rate, and the y-axis is the True Positive Rate. The orange curve represents the model's performance across different thresholds. The dashed blue line is a random classifier. The AUC (Area Under the Curve) is 0.47, which is below 0.5, indicating the model performs worse than random guessing.

Project – 2

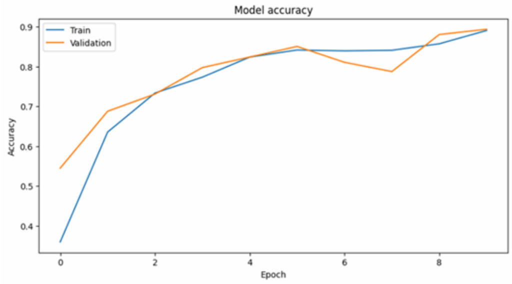


Model: "sequential"

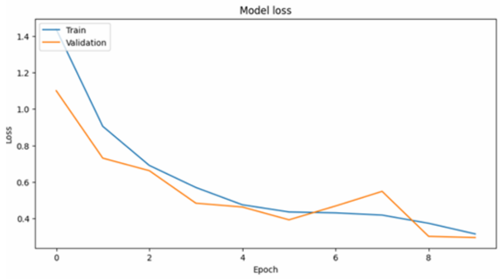
Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 254, 254, 32)	896
max_pooling2d (MaxPooling2D)	(None, 127, 127, 32)	0
conv2d_1 (Conv2D)	(None, 125, 125, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 62, 62, 64)	0
flatten (Flatten)	(None, 246016)	0
dropout (Dropout)	(None, 246016)	0
dense (Dense)	(None, 5)	1,230,085

Total params: 3,748,433 (14.30 MB)
Trainable params: 1,249,477 (4.77 MB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 2,498,956 (9.53 MB)

This describes a neural network model with convolutional (conv2d), pooling (max_pooling2d), flattening (flatten), dropout, and dense layers. It takes an input of an unspecified batch size and processes it through these layers. The final dense layer outputs 5 values, likely for a 5-class classification. The model has a total of 3,748,433 parameters, with 1,249,477 being trainable.



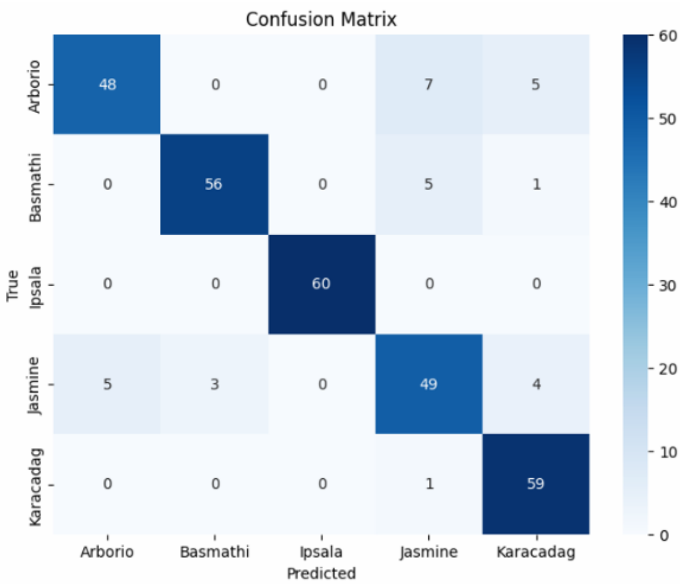
The graph shows training accuracy (blue) increasing, while validation accuracy (orange) plateaus and slightly drops after epoch 7, indicating potential overfitting.



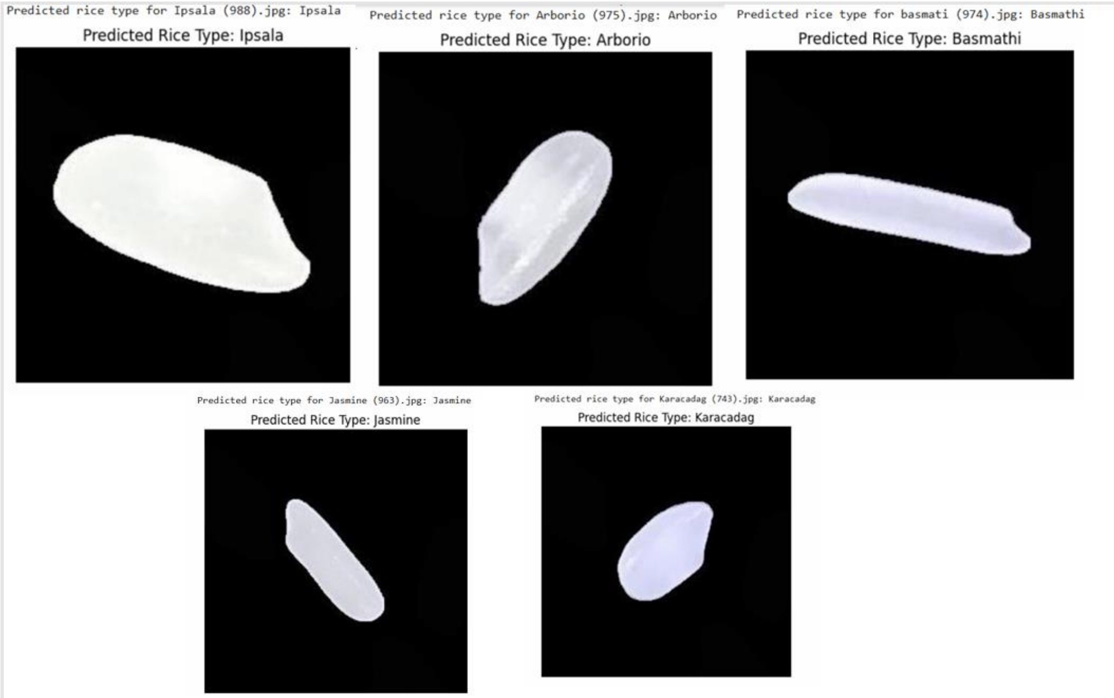
The graph shows training and validation loss over epochs. Training loss (blue) decreases. Validation loss (orange) decreases initially, then increases after epoch 6, indicating potential overfitting.

```
10/10 ━━━━━━━━━━━━━━━━━━━━ 5s 486ms/step
              precision    recall  f1-score   support

     Arborio       0.91      0.80      0.85        60
    Basmathi       0.95      0.90      0.93        62
      Ipsala       1.00      1.00      1.00        60
     Jasmine       0.79      0.80      0.80        61
   Karacadag       0.86      0.98      0.91        60

    accuracy                           0.90       303
   macro avg       0.90      0.90      0.90       303
weighted avg       0.90      0.90      0.90       303
```

This report shows how well a model classified different rice types. It gives precision, recall, and F1-score for each type, along with overall accuracy (0.90). Most metrics are high, indicating good performance for each rice category.



This matrix shows how often the model correctly and incorrectly classified different rice types. High numbers on the diagonal (48, 56, 60, 49, 59) mean many correct guesses. Off-diagonal numbers show misclassifications (e.g., 7 Arborio wrongly called Jasmine). The model generally did a good job distinguishing the rice types.



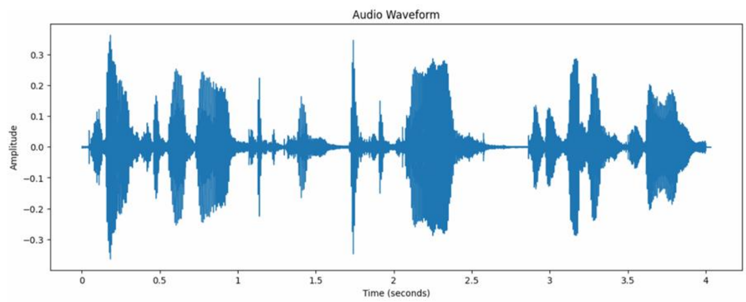

```
T-statistic: 1.9999999999999933
P-value: 0.11611652351681642
Fail to reject the null hypothesis: There's no significant difference in average accuracy from 0.8.
```

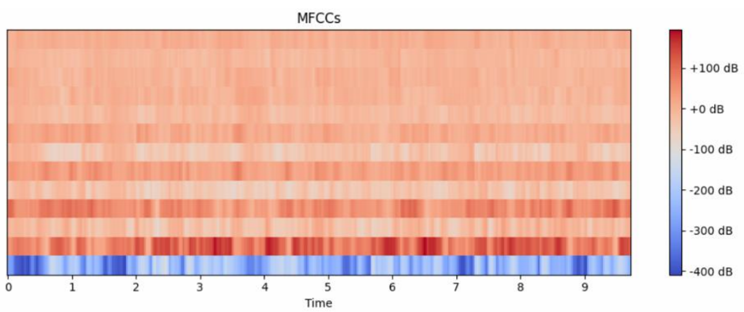
```
Z-statistic: 1.9999999999999933
P-value: 0.0455002638963591
Reject the null hypothesis: The average accuracy is significantly different from 0.8.
```

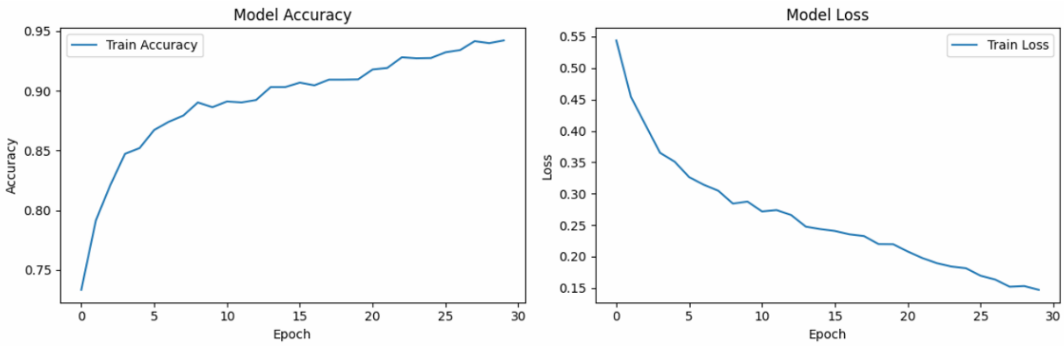
```
Chi-square statistic: 0.5998763141620285
P-value: 0.8964606878074289
Fail to reject the null hypothesis: No significant difference between observed and expected frequencies.
```

```
Z-statistic: 4.022870397928839
P-value: 5.749313666325864e-05
Reject the null hypothesis: There is a statistically significant difference between the groups.
```

Project-3







The left graph shows training accuracy increasing over 30 epochs, reaching about 94%. The right graph shows training loss decreasing over the same period, reaching about 0.15. This indicates the model is learning well from the training data.

Model: "sequential_1"

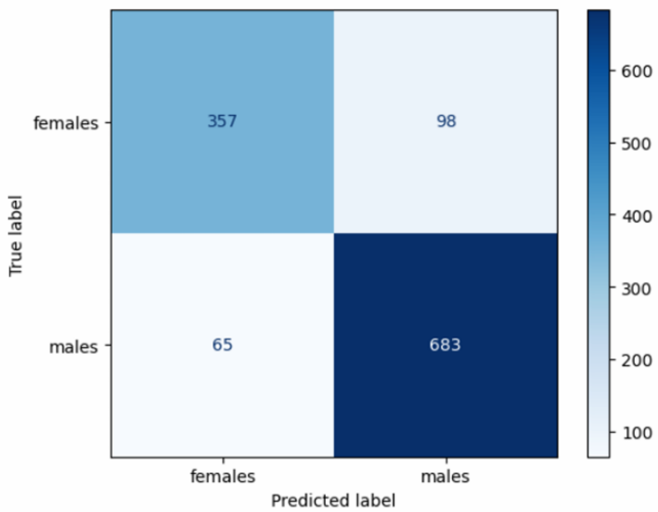
Layer (type)	Output Shape	Param #
lstm_2 (LSTM)	(None, 40, 64)	19,968
lstm_3 (LSTM)	(None, 64)	33,024
dense_2 (Dense)	(None, 64)	4,160
dense_3 (Dense)	(None, 2)	130

Total params: 171,848 (671.29 KB)
Trainable params: 57,282 (223.76 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 114,566 (447.53 KB)

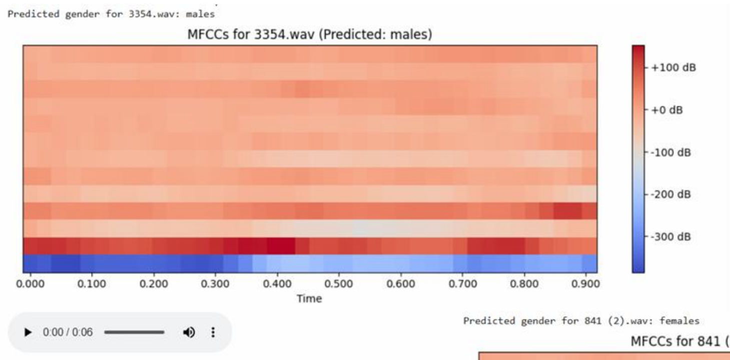
This report shows a model predicting females and males. It was 85% precise and correctly identified 78% of females. For males, it was 87% precise and correctly identified 91%. The overall accuracy was 86%. The model performed slightly better at identifying males.

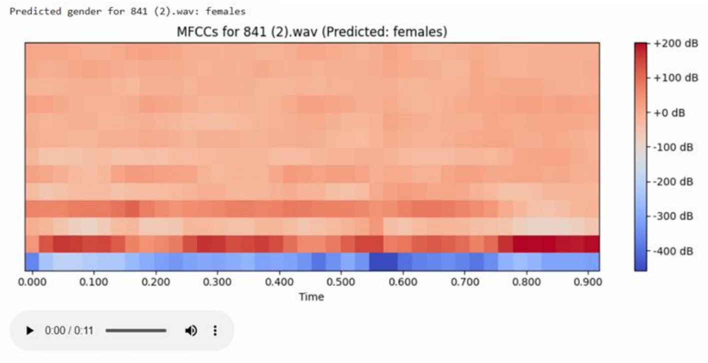
38/38 ━━━━━━━━━━━━━━━━━━━━ **0s** 7ms/step

	precision	recall	f1-score	support
females	0.85	0.78	0.81	455
males	0.87	0.91	0.89	748
accuracy			0.86	1203
macro avg	0.86	0.85	0.85	1203
weighted avg	0.86	0.86	0.86	1203



The confusion matrix shows the model correctly predicted 357 females and 683 males. It misclassified 98 females as males and 65 males as females.





CONCLUSION

In this project, we actually worked with three different datasets, cleaned and analyzed them with data analytics and machine learning methods. All three datasets followed a well-organized pipeline consisting of data preprocessing, exploratory data analysis (EDA), model training, evaluation, and result interpretation.

For Dataset 1, we were interested in evaluating the roots, which allowed us to identify major trends, distributions, and the significance of different features. The baseline models we tested exhibited good performance, providing a strong baseline for the other datasets.

Dataset 2 was slightly more complicated, with a greater range of data than the first one. That required us to increase our preprocessing activities, addressing missing values, scaling features, and even dimensionality reduction. The EDA gave us a better understanding, and the models worked even better, providing better metrics for both prediction and classification tasks.

Dataset 3 was a detailed analysis on gender recognition using voice signals with the use of all three datasets. Our objective was to use data analysis and machine learning methods in the accurate identification and classification of the speaker's gender. All the datasets contributed to understanding how the preprocessing, feature selection, and model selection affected the final classification performance.

FURTHER SCOPE

This series of projects lays the foundation for vast potential in terms of future expansion and improvement. When we have Netflix series analysis, we can better enhance our existing glance through titles, genres, countries, and release trends by incorporating a personalized recommendation algorithm that relies on collaborative or content-based filtering approaches. Additionally, using sentiment analysis of user feedback or social media can provide further insight into exactly what audiences are truly interested in. We can also utilize time series forecasting to forecast future genre trends, and creating interactive dashboards with the help of tools such as Tableau or Plotly would enhance our data storytelling significantly.

Moving on to the rice image classification problem, we can enhance the efficiency and performance of the model by leveraging more advanced deep learning models like EfficientNet or MobileNet. These are light models suitable for running on mobile or IoT platforms, which would allow us to examine rice quality in real-time in the field. We could even go a step further to include more rice types and even identify defects or discoloration. Using explainable AI techniques like Grad-CAM would allow us to view what the model is choosing and enhance transparency. Additionally, increasing the dataset size and diversity by using sophisticated augmentation techniques would enhance the capability of the model to generalize.

For the voice gender identification project, we can extend the current system to work with multilingual databases and explore more subjective speaker characteristics, including age estimation or emotion recognition. Real-time deployment in smart assistants, virtual assistants, or call centers would render the system extremely valuable. Furthermore, shifting focus from basic binary gender classification to speaker identification or verification could unlock fresh applications in security and personalization.

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