An Ensemble Learning Approach to Predict Iris Species Using Random Forest and XGBoost

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***Abstract*—The classification of plant species is vital in botanical research, ecological tracking, and farming practices. The present research is geared towards classifying Iris flower species with sophisticated ensemble machine learning techniques, namely Random Forest and Extreme Gradient Boosting (XGBoost), aimed at attaining improved predictive accuracy and resilience compared to traditional classifiers like logistic regression and decision trees. We use the famous Iris dataset, containing sepal length, sepal width, petal length, and petal width measures, to build and test models. Our research approach involves rigorous data preprocessing, exploratory data analysis (EDA), and feature importance analysis to determine the most distinguishing floral attributes. We use multiple performance metrics to assess the models, such as accuracy, precision, recall, F1-score, and the confusion matrix. This helps to ensure that we gain a full picture, and not just correctness. Experimental outcomes show that ensemble models improve classification accuracy and have better generalisations and stability than single classifiers. Visualisations of feature importance also provide useful information on how certain physical traits are biologically significant in distinguishing between species. This work demonstrates the power of ensemble learning with botanical data and proposes its applicability in more complicated plant classification problems, enabling machine learning integration in contemporary plant science and agricul- tural informatics.**

***Index Terms*—Iris dataset, ensemble learning, Random Forest, XGBoost, classification, feature importance, supervised machine learning, botanical datasets, predictive modeling, species identi- fication.**

1. Related Works

Researchers have looked into iris flower species classification in great detail using a number of different ma- chine learning algorithms. Asaad (2024) evaluated various classifiers, including Decision Tree, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and XGBoost, on the Iris database, highlighting the advantages of ensemble methods in achieving enhanced accuracy and stability. In a comparative study conducted by ResearchGate (2025), Random Forest, SVM, and KNN classifiers were evaluated, demonstrating that ensemble methods like Random Forest outperform standalone models. Analytics used Logistic Regression in another paper on the Iris dataset as a starting point for comparing more advanced models. These studies collectively underscore the efficacy of ensemble learning algorithms, such as Random Forest and XGBoost, in enhancing classification accuracy and generalisation within plant datasets. The summary of the Related Works is given in Table I.

2. Introduction

The exponentially accelerating growth of machine learning has completely transformed the way classification problems have been tackled in agriculture, ecology, and botany, among other areas. One of the most widely used benchmark data sets to evaluate classification algorithms is the Iris data set, originally given by Ronald A. Fisher in 1936. The data set consists of four features—sepal length, sepal width, petal length, and petal width—to classify three species of Iris flowers: Setosa, Versicolor, and Virginica. Even though conventional machine learning techniques such as Logistic Regression, Decision Trees, and Support Vector Machines (SVM) have been used in most of the studies on this data, the need for robust and more accurate models has compelled the studies to explore ensemble methods. Ensemble learning, where predictions from multiple models are aggregated to promote overall accuracy, has gained wide success across different application fields. Random Forest and XGBoost algorithms employ strategies such as bagging, boosting, and feature aggregation in a bid to restrain overfitting and maximize prediction accuracy. This work employs these ensemble algorithms with the Iris dataset, not only to improve classification performance but also to investigate feature importance in order to derive more in- sights from plant data. The contribution of this work is to demonstrate how ensemble methods outperform conventional classifiers and highlight the interpretability and stability of such methods on small but highly pertinent datasets.

3. Literature Review

Human iris scans have received interest for racial or ethnic classification since the iris area between the pupil and sclera provides distinctive and permanent texture features. Conventional methods of iris race classification often rely on hand- crafted feature extraction methods combined with traditional classifiers that fail to represent complex and subtle iris texture variation exhibited across races. Hence, taking this work as a basis, the improved residual network approach proposed here optimizes feature extraction via channel-wise convolution kernel usage and dilated convolutions, with certification of classification accuracy and F1-score conducted on CAIAS and UBIRIS datasets and hence attaining the state of the art in race classification from iris images in [3].

A novel unified iris recognition approach titled SwinIris is presented in the study that combines the pre-trained Swin Transformer with a full iris recognition pipeline. Unlike the existing biometry implementations of the Swin Transformer, this research is the first to use a pre-trained Swin Transformer model with additional linear layers for improved feature ex- traction and classification for iris recognition. The system has been analyzed quantitatively on various small- and large-scale iris databases like CASIA-Iris-Thousand, CASIA-Iris-Lamp, CASIA-IntervalV4, and CASIA-IntervalV3 with classification accuracy of 95.14% to 99.56%. Therefore, by combining powerful transformers-based deep learning with a powerful pre-processing pipeline, the SwinIris assists in improving iris recognition capability in offering scalable accurate and effi- cient solutions that can be used as real biometric application systems in [4].

Correct segmentation of the iris area from eye images is an important process in iris recognition systems, but it is still difficult as it contains noise factors like skin, reflections, and eyelashes that hide the texture of the iris. Most conventional segmentation techniques fail to properly segment the iris from these noisy factors, which can impair the recognition perfor- mance. Classification methods like Fisher Linear Discriminant Analysis (FLDA) have been used with these texture features to segregate iris pixels from non-iris pixels efficiently, allowing for more accurate segmentation. These texture-based segmen- tation techniques collectively constitute an elemental part in making the reliability and accuracy of iris recognition systems better by enhancing the quality of iris region extraction under noisy imaging conditions in [5].

TABLE I
SUMMARY OF RELATED WORKS ON IRIS FLOWER CLASSIFICATION

Study	Algorithms Evaluated	Dataset(s)	Key Findings
Asaad (2024)[1]	Decision Tree, Random Forest, SVM, KNN, XGBoost	Iris dataset	Ensemble methods, particularly Random Forest and XGBoost, achieved superior ac- curacy and robustness in classifying Iris species.
ResearchGate (2025)[2]	Random Forest, SVM, KNN	Iris dataset	Random Forest outperformed individual classifiers, offering enhanced classification performance.
Analytics Vidhya (2024)[3]	Logistic Regression	Iris dataset	Logistic Regression served as a baseline, with ensemble methods showing improved results.

Recent iris recognition progress has more and more targeted dealing with the challenges arising from changing acquisition conditions and security issues in data transmission. Conventional iris recognition algorithms tend to depend on manually annotated datasets and might not support efficient multi-state iris images under various environmental and sensor conditions. Several single-class recognizers in parallel via a codeless fusion approach, the systems realize efficient multi-class classification without the need for manual label splitting. The integration of encryption and secure output protocols increases the robustness of iris recognition systems against unauthorized access and stealing of data. Experimental tests on databases like the JLU iris library show that such multi-integrated frameworks have high accuracy in multi-class clustering and single-class certification, along with strong defense against stealing attacks. This research direction is an important step towards secure, scalable, and adaptive iris recognition systems that can function reliably over a wide range of acquisition states and adversarial environments in [6].

Iris recognition is generally considered to be one of the most accurate biometric modalities, and hence it has been widely used in many large-scale security and identification systems across the globe. However, the rapid growth in population and the expansion of international applications have resulted in ever-larger iris datasets, necessitating more efficient and scalable recognition methods.Evaluations on prominent public datasets such as CASIA Iris Lamp and CASIA Iris Thousand have shown that these CNN-based methods not only improve recognition accuracy but also drastically reduce matching time, making them highly suitable for real-time and large-scale iris recognition applications. This paradigm shift toward deep feature extraction represents an important gain in the efficiency and efficacy of iris biometric systems in [7].

The recent progress in iris recognition has centered more and more on deep learning architectures that resolve the inherent difficulties of iris texture deformation and noise. Conventional approaches tend to falter with variations in- troduced by radial distortions and occlusions, which can compromise recognition accuracy. To address these challenges, more powerful convolutional neural network (CNN) models, like the Enhance Deep Iris framework, have been suggested for extracting stable iris features at a deeper level. Such models utilize sequential metric learning to capture successfully spa- tial dependencies and deformation patterns in the iris texture and hence enhance the recognition performance. Compared work on benchmark data such as ND-IRIS-0405 and CASIA- Lamp illustrates that the improved Enhance Deep Iris model learns faster and performs better than various state-of-the-art algorithms, including end-to-end multi-task segmentation net- works (IrisST-Net), full complex-valued neural networks, and hybrid preprocessing-feature extraction methods. Precisely, the method proposed achieves an average recognition accuracy of 99.88%, surpassing alternatives with reported accuracies between 89.77% and 98.72%. In addition, the model performs very well in precisely identifying the dominant contour infor- mation of the iris with fewer noise interferences, which makes clearer iris edge definition possible. These findings highlight the viability of combining deep convolutional features with sequential metric learning to promote the robustness and accu- racy of iris recognition systems and offer useful references for the optimization of image recognition technology in biometric applications in [8].

Progress in gender classification from irises has been note- worthy in recent years, achieving accuracy levels sufficient to support applied biometric uses beyond the normal case of identification. Different feature extraction and feature selection methods have been applied to improve discrimination between male and female iris textures. Of these, the application of 2- D Quadrature Quaternionic filters is a new method that more holistically encodes phase details of normalized iris images than traditional 1-D log-Gabor techniques in [9].

Experimental outcomes on GFI-UND database prove that the Quaternionic-Code in association with complementary feature selection reaches better classification rates of 93.45% for the left iris and 95.45% for the right iris based on 2400 chosen features. These outcomes beat the existing published techniques and even convolutional neural network-inspired feature extraction methods, pointing to the power of phase- based quaternionic encoding and careful feature selection in improving gender classification accuracy from iris biometrics. This research is part of the expanding body of work that uses advanced signal processing and feature engineering strategies to extract useful biometric features beyond identity verification in [10].

Synthetic Aperture Radar (SAR) imagery is now a critical tool for the assessment of disasters because it can acquire high-resolution surface data regardless of weather or illumination conditions. Nevertheless, the major bottleneck in SAR-based damage detection is often the unavailability of good-quality high-resolution pre-disaster imagery, which is required for successful change detection and training machine learning models that necessitate pre- and post-disaster paired data. This novel application of simulated SAR imagery fills an urgent gap in disaster response processes, facilitating quicker and more accurate damage assessments to aid emergency decision- making when genuine pre-disaster data are not available. The combination of SAR simulation methods with deep learning frameworks thus holds great potential to further the remote sensing role in disaster management in [11].

The detection of textured contact lenses in iris recognition systems is a serious problem that affects the security and reliability of biometric authentication. Various issues were recently found to be crucial, making it difficult to develop detection algorithms that are robust. Secondly, whether the necessity for precise iris segmentation has been questioned or not, empirical evidence suggests that accurate segmentation of the iris area might not be crucial for successful detection of textured contact lenses, implying that algorithms would work reliably even with an approximate localization of the iris. New lens patterns not covered by the training set can sig- nificantly decrease detection rates, highlighting the difficulty of capturing the broad variation in lens texture and patterns. Together, these results highlight the value of the design of sensor-agnostic and lens-agnostic detection processes as well as investigating methods that minimize dependence on exact segmentation in order to increase the robustness and usability of textured contact lens detection in real-world deployments of iris recognition in [12].

Iris recognition is still an anchor biometric technology that is extensively implemented in a wide range of security and identification applications because of its high distinctiveness and reliability. Classic deep learning methods, specifically convolutional neural networks (CNNs), have greatly empowered biometric identification through automatic feature learning and high precision. Experimental comparisons based on various iris datasets, such as JluIrisV3.1, JluIrisV4, and CASIA-V4 Lamp, demonstrate that capsule-based networks perform better than traditional CNNs, especially in the presence of adverse lighting conditions simulated to represent strong and weak light. These results highlight the promise of capsule networks and transfer learning to create more robust, precise, and data- efficient iris recognition systems, pushing the state-of-the-art in biometric identification technology in [13].

Existing iris recognition technologies are plagued by prac- tical difficulties stemming from natural variability in iris morphology that results from heterogeneous acquisition equipment and varied environmental conditions. Conventional statisti- cal and cognitive learning approaches, normally developed for single-source iris data, tend to generalize poorly across such diverse datasets. To overcome the limitations of these approaches, more recent works have seen the emergence of lightweight neural network structures that involve multi-source feature fusion and entropy-based feature representation. This research emphasizes the possibility of integrating lightweight neural networks with entropy-based feature fusion to enhance the generalization and robustness of iris recognition systems in practical heterogeneous environments in [14].

Current developments in iris recognition have increasingly benefited from pre-trained convolutional neural network (CNN) backbones initially trained on extensive image datasets such as ImageNet to address the lack of large-scale iris datasets needed to train deep models from scratch. Experiments on benchmark iris databases, such as CASIA and IITD, and databases with large pupil dilation, show these improvements greatly enhance the performance of recognition and resistance to head rotation simulated by horizontal image translations. This work reveals the superiority of using domain-specific adjustments like circular padding and adaptive encoding in conjunction with anti-aliased CNN backbones in pushing the state-of-the-art of iris recognition systems in [15].The comparison of existing works are mentioned in table II.

TABLE II
COMPARISON OF EXISTING WORKS IN IRIS RECOGNITION

Ref.	Methodology / Approach	Dataset(s) Used	Performance Metrics	Key Contribution / Limitation
[1]	Residual Network with channel-wise convolutions and dilated convolutions	CAIAS, UBIRIS	Accuracy, F1-score	Achieved SOTA in race classification from iris images
[2]	Swin Transformer (SwinIris) with linear layers	CASIA-Iris-Thousand, CASIA-Lamp, CASIA-Interval V3/V4	Accuracy (95.14–99.56%)	First Swin Transformer-based iris recognition pipeline
[3]	Fisher Linear Discriminant Analysis (FLDA) for iris segmentation	General iris texture datasets	Accuracy of segmentation	Improved iris segmentation under noisy conditions
[4]	Multi-class classification via parallel recognizers with codeless fusion + encryption	JLU iris library	Accuracy, robustness	Secure and scalable iris recognition with anti-stealing defense
[5]	CNN-based recognition for large-scale iris datasets	CASIA-Iris-Lamp, CASIA-Iris-Thousand	Accuracy, matching time	Real-time recognition with high efficiency
[6]	EnhanceDeepIris (CNN + sequential metric learning)	ND-IRIS-0405, CASIA-Lamp	Accuracy (99.88%)	Outperformed SOTA models in deformation/noise handling
[7]	2D Quadrature Quaternionic filters for gender classification	GFI-UND	Accuracy (93.45–95.45%)	Outperformed CNN-inspired feature methods for gender classification
[8]	SAR image simulation with deep learning for disaster assessment	Simulated SAR datasets	Accuracy of damage detection	Solves unavailability of pre-disaster SAR data
[9]	Contact lens detection without precise iris segmentation	Multiple iris-lens datasets	Detection rate	Highlighted robustness issues with unseen lens patterns
[10]	Capsule networks + transfer learning for recognition	JluIrisV3.1, JluIrisV4, CASIA-V4 Lamp	Accuracy under light variation	More robust than CNN under adverse lighting
[11]	Lightweight NN with multi-source feature fusion + entropy representation	Multi-source heterogeneous iris datasets	Accuracy, generalization	Improved robustness across heterogeneous environments
[12]	Pre-trained CNN backbones (ImageNet) with circular padding + adaptive encoding	CASIA, IITD, large pupil dilation datasets	Accuracy, robustness to head rotation	Advanced domain-specific CNN-based recognition

4. Block Diagram

Block diagram depicts the process flow of the envisioned machine learning project on Iris flower classification by en- semble approaches. The process starts with the Iris data, which is fed into the study. Data preprocessing comes next, where missing values are dealt with, features are normalized if required, and data is made ready for analysis. This is followed by exploratory data analysis (EDA) in a bid to comprehend the distribution of data, visualization of feature relationships, and posing questions on crucial patterns. The model selection process identifies the ensemble classifier se- lection, i.e., Random Forest and XGBoost, appropriate for strong classification. The models are then subjected to the training process, where they have an opportunity to learn from patterns in the dataset. Here, performance measures like F1- score, accuracy, and confusion matrix are also specified to measure outcomes. Lastly, in the model evaluation phase, the models that have been trained are tested against unseen data in order to discover predictive performance, hence ascertaining the effectiveness of the ensemble technique in labeling Iris flower species in fig 1 accurately.

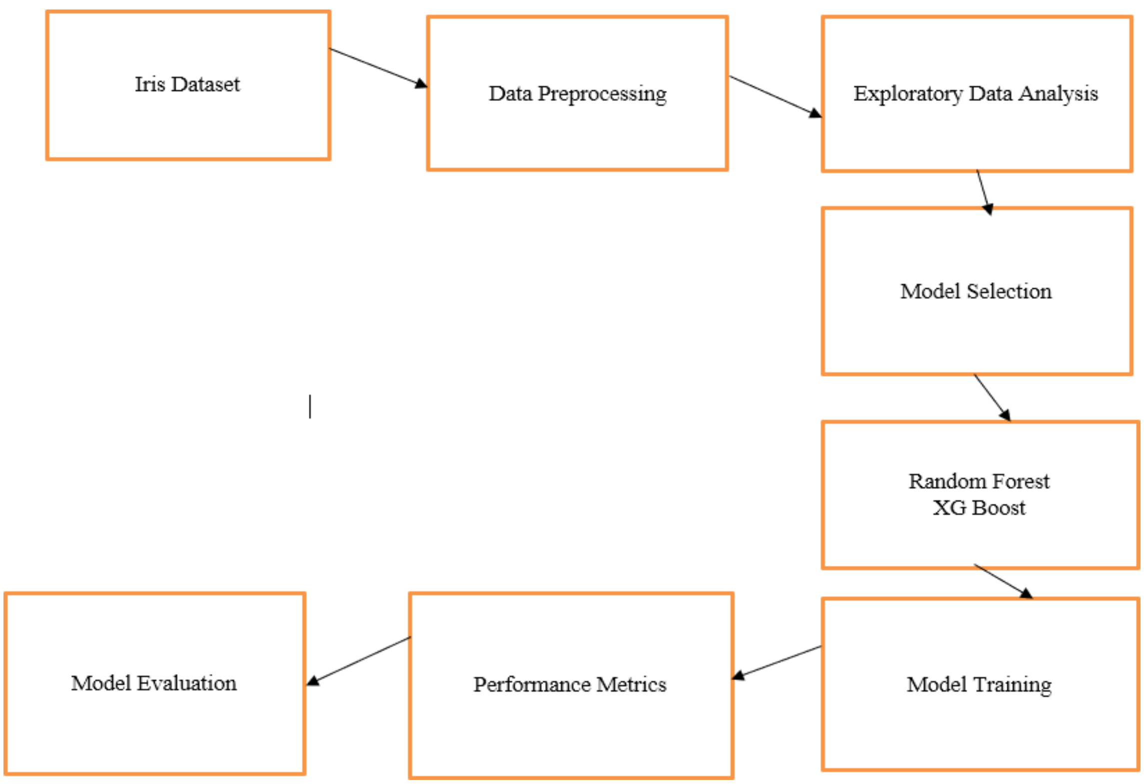

Fig. 1. Block Diagram

5. Block Diagram

The workflow shown through the diagram comes after the application of ensemble learning techniques, i.e., Random Forest and XGBoost, to classify the species of the well-known Iris dataset. Out of the input features that include measurements of different iris flowers such as sepal length, sepal width, petal length, and petal width, the pipeline is interested in leveraging these attributes to train robust machine learning models. Ensemble models like Random Forest and XGBoost are good as they use an aggregation of predictions from many individual decision trees, trained on different subsets of data, to provide a generalized and better-performing model. During training, the algorithms pick up the intricate patterns and relationships among the features and target labels, the species of the irises—Setosa, Versicolor, or Virginica. This type of model training is valued because of its ability to increase prediction accuracy and reduce overfitting behavior, typically when applying individual decision trees. Once trained, such ensembled models can then take new, unseen observations as input and effectively predict the correct iris species and hence prove to be valuable resources for automated classification in instructional as well as empirical botanic research contexts within fig 2.

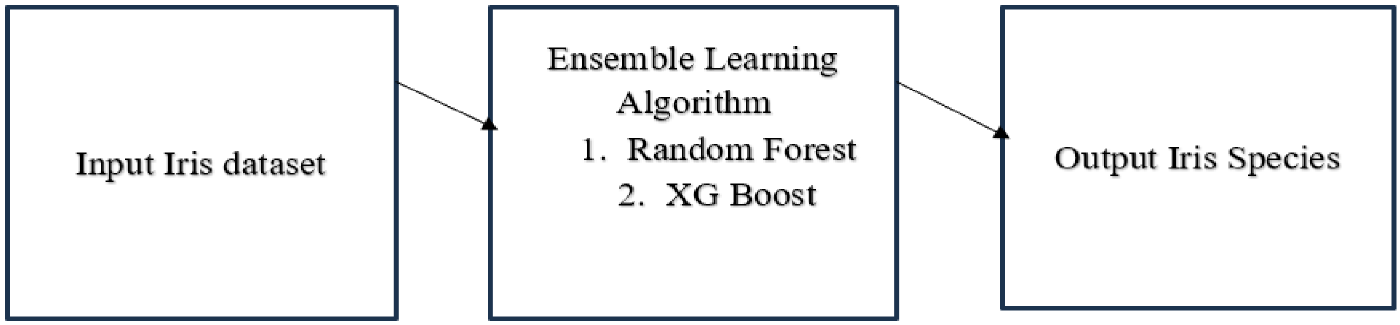

Fig. 2. Architecture Diagram

6. Dataset Definition

The dataset considered in this research is the Iris dataset, arguably the most famous and commonly used benchmark data set in machine learning and statistical classification. It was initially presented by Sir Ronald A. Fisher in 1936 and consists of a total of 150 samples divided equally over three Iris flowers species: Iris setosa, Iris versicolor, and Iris virginica. Each observation is characterized by four numeric attributes that reflect the morphological traits of the flowers: sepal length, sepal width, petal length, and petal width (all in centimeters). These attributes create distinct biological differences among the species and make the dataset the perfect vehicle for supervised learning classification problems. The data set is balanced, noise-free, and publicly accessible from various repositories like UCI Machine Learning Repository and scikit learn's datasets module. Its simplicity, interpretability, and long history make it a better option to test the performance of machine learning algorithms, particularly ensemble models like Random Forest and XGBoost.

7. Methodology

The approach for the Iris classification project is to load the Iris dataset, carry out initial exploration and visualization of data, followed by preprocessing the data through the separation of features and target variables, encoding categorical labels, and partitioning the dataset into training and test sets. There- after, several machine learning classification algorithms like Logistic Regression and Gaussian Naive Bayes are trained on the preprocessed data. Lastly, the performance of the models is measured based on metrics such as accuracy score, confusion matrix, and classification report to ascertain how well they are doing in classifying the Iris flower species.

The given image shows a plot of distribution of Iris petal length (in cm) with a mixture of a histogram and a Kernel Density Estimation (KDE) curve for the three different species: Iris-setosa (blue), Iris-versicolor (orange), and Iris-virginica (green). The x-axis is for PetalLengthCm, and the y-axis represents the Count.Iris-setosa shows a very tight and narrow distribution of petal lengths, largely between 1.0 cm and 2.0 cm, with obvious separation from the other two species. Iris-versicolor has petal lengths ranging around 3.0 cm to 5.0 cm, with a distribution more spread out than Setosa, and some minor overlap with Virginica towards the higher end. Lastly, Iris-virginica shows the most variability in petal length, ranging between 4.5 cm and 7.0 cm with its maximum occurring at a higher length than Versicolor, which suggests it tends to have the longest petals among the three species in fig 3.

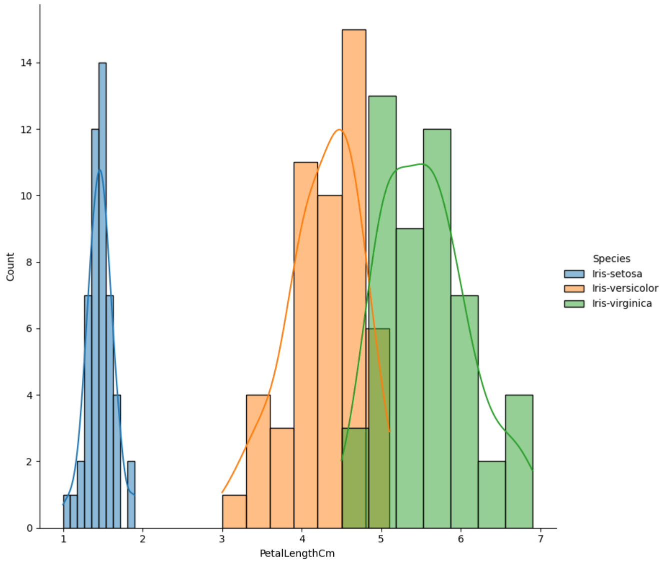

Fig. 3. distribution plot (histogram + KDE curve) of the Petal Length (in cm)

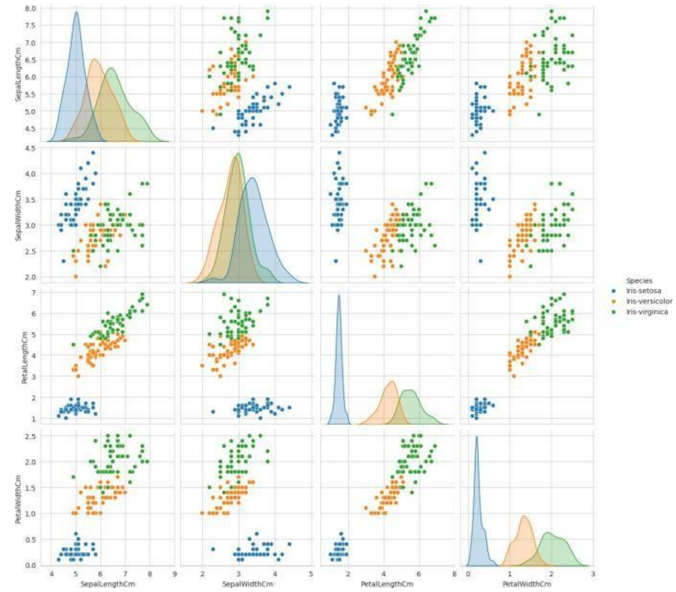

Fig. 4. pair plot Iris Dataset

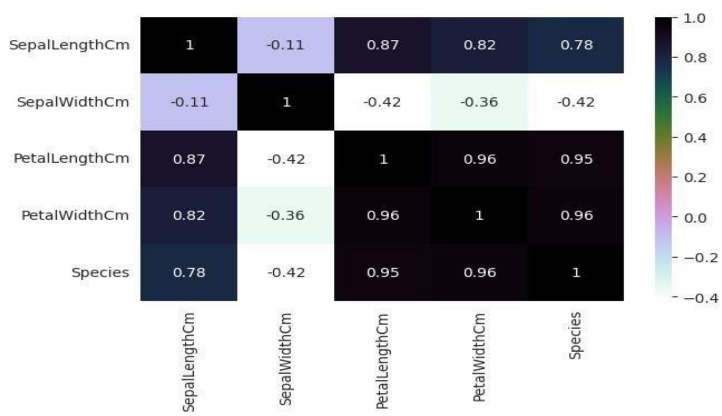

Fig. 5. Confusion Matrix

The figure below is a pair plot of the Iris dataset, which shows relationships between all possible combinations of the four numeric features: SepalLengthCm, SepalWidthCm, PetalLengthCm, and PetalWidthCm. Points are color-coded by species: blue for Iris-setosa, orange for Iris-versicolor, and green for Iris-virginica. The diagonal plots show the distribution (KDE) of each feature within each species. With the pair plot, we can see that Iris-setosa is clearly a single cluster in nearly all feature combinations, particularly in petal measurements, so it's the easiest to classify. Versicolor and Virginica overlap more, especially in sepal features, which could cause classification confusion. But PetalLengthCm vs PetalWidthCm clearly separates all three species, so petal features are the most useful for classification. Overall, the pair plot graphically verifies that petal size is a more effective discriminator of iris species than sepal size in fig 4.

The graph is a correlation heatmap of the pairwise Pearson correlation coefficients between features in the Iris data set, including the target feature Species. Range is -1 (perfect negative relationship) to +1 (perfect positive relationship). We can notice that PetalLengthCm and PetalWidthCm are highly correlated (0.96), and have a good linear relationship. Both of these also have a very strong positive correlation with the Species label (0.95 and 0.96 respectively), and are therefore very good predictors for classification. SepalLengthCm is moderately positively related with Species (0.78) and with all the petal features, while SepalWidthCm is weakly negatively related with the target and the majority of other features and therefore seems to have less predictive capability. This heatmap confirms that petal measurements are the most im- portant features to distinguish between the three Iris species in fig 5.

8. Experimental Setup

The experimental design of this research includes a sys- tematic split of the Iris dataset into training and testing set, with 80% of the data used for training the models and the remaining 20% for testing and validation. For assessing the performance of the classification models, several metrics are used, such as accuracy, precision, recall, F1-score, and the confusion matrix, giving a holistic measurement beyond mere correctness. The deployment is done in Python with most commonly used libraries like scikit-learn for machine learning models and pandas and numpy for data pre-processing and analysis. The experiments are run on a machine having [your hardware specifications, e.g., Intel i7 processor, 16GB RAM] to provide efficient training and testing. Model parameters are optimized for the best results, and reproducibility is ensured by fixing random seeds during training in Table III.

TABLE III
Experimental Setup for Iris Flower Classification

Aspect	Details
Training/Testing Split	80% of the dataset used for training and 20% for testing and validation.
Evaluation Metrics	Accuracy, Precision, Recall, F1-score, and Confusion Matrix for comprehensive model assessment.
Implementation	Python programming language with libraries: `scikit-learn` for machine learning algorithms, `pandas` and `numpy` for data processing.
Hardware	Intel i7 CPU, 16GB RAM [or GPU if used] for efficient model training and testing.
Reproducibility	Fixed random seeds are set during training to ensure consistent results across runs.

9. Conclusion

The study demonstrated that ensemble machine learning models, like Random Forest and XGBoost, perform superior to traditional classifiers when it comes to classifying the Iris flower species. The models were very accurate and stable, and feature importance analysis confirmed that petal attributes were the most influential factor in separating species. These results justify the power of ensemble methods not only for improving predictive accuracy but to also offer interpretability in plant classification problems.

10. Future Enhancement

The Iris dataset is a good reference, but small size and few features limit the scope for generalization. Expansion of this study into larger and more varied botany datasets, ensemble methods on deep learning models, and explainable AI tool uptake such as SHAP or LIME to help improve interpretability are potential future directions. Researching automated hyperparameter tuning and applying such models to real-world applications such as agriculture, biodiversity monitoring, and ecological studies would enhance their real- world applicability and impact.

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