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Tomato Leaf Disease Detection and Classification Using Convolutional Neural Network and Machine Learning

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Abstract: Tomato is one of the most important horticulture crops in the world, however, it faces many important threats due to different diseases which may deteriorate the yield quality and loss. For management of efficient crop and reasonable yield, rapid and precise disease identification is very important. This study has made elaborate comparison between the conventional machine learning and deep learning for the classification of Tomato leaves images. This dataset has a total of 30000 images of 10 different types of diseases and healthy condition of Tomato leaves. The segmentation has been made for each disease as Bacterial-Spot (BS), Early-Blight (EB), Healthy, Late-Blight (LB), Leaf-Mold (LM), Septoria-Leaf-Spot (SLS), Spider-Mites-Two-spotted-Spider-Mite (SMTSSM), Target-Spot (TS), Tomato-Mosaic-Virus (TMV) and Tomato-Yellow-Leaf-Curl-Virus (TYLCV). A Convolutional Neural Network (CNN) is applied which consists of four convolutional layers, max pooling, a fully connected layer, dropout for regularization and a softmax layer for class probability. The classic machine learning techniques such as adaBoost classifier (ABC), K-nearest neighbor (KNN), random forest classifier (RFC), and naïve bayes (NB) has also been examined. Our experiment showed that the CNN is significantly better than the classic classifiers, it was able to able to obtain 96% accuracy whereas the classic classifiers gave poor accuracy, ABC 52%, KNN 56%, RFC 71% and NB 49%.

Keywords: Tomatoes Leaf; Disease Classification; CNN; Deep Learning.

1. Introduction

Tomatoes are a global staple, playing a crucial role in both economies and human nutrition in agriculture. In addition to being a primary food source, their cultivation and yield have enormous implications for global food security (Andrew et al., 2022). Tomato crops are under constant threat from various diseases, which can lead to severe economic loss and diminishing food supply (Hornyák & Iantovics, 2023). Reliable and efficient disease detection systems are needed, as conventional methodologies that primarily rely on human visual inspection have been shown to be time-inefficient and inconsistent in disease detection (Simonyan & Zisserman, 2014). Our work leverages state of the art Convolutional Neural Networks (CNNs) and machine learning algorithms to create an efficient and accurate detection and classification system for tomato leaf diseases. This work has far-reaching potential for reforming the way agriculture is conducted, allowing for both earlier detection and more precise identification of agricultural crop disease and hence a more directed and timely intervention to reduce crop loss (James et al., n.d.). This study not only contributes to improving tomato produce but also tackles the challenge of handling uneven data in machine learning, a common obstacle in accurate disease classification (Saleem et al., 2020). We compare the performance of the CNNs with traditional machine learning techniques including adaBoost classifier, K-nearest neighbor, random forest classifier, and naïve bayes, bringing these data comparisons and techniques to bear on a very real problem facing agriculture today, in many ways bridging that technology gap (Sakkarvarthi et al., 2022). The methodology in this work could be expanded to work on even more leaf datasets, that are quite prevalent in plant classification in agriculture (Lecun et al., 2015). This work may help in providing better decision-making mechanisms for plant disease treatment, and so may have additional implications for increased food production. The work on disbalanced data in machine learning a common problem when dealing with plant disease identification — alone would be enough to make this an interesting research problem in moving forward in effective ways to help farmers improve farming.

2. Related Work

The amalgamation of agricultural technology and artificial intelligence has received an influx of interdisciplinary research, notably, in the domain of disease detection and classification via image analysis. Researchers have employed the use convolutional neural networks (CNNs) convincingly in the past for plant disease classification, which is indicative of their ability to identify complex patterns within leaf images (Pedregosa et al., 2012). For a relevant example, CNNs were employed by (Sundararaman et al., 2023) to discern foliar diseases in numerous crops thanks to their frontline work in processing intricate leaf images. Likewise, (Goodfellow et al., n.d.) conducted an analysis comparing the accuracy of CNNs to traditional image processing techniques in the realm of plant disease detection, and concluded that CNNs offer a marked improvement to the way researchers are able to detect them. (Chollet, n.d.), similarly, worked on the identification tomato crop maladies, and managed to get his CNN model to detect early and late blight using only 93% of the time, proving just how potent of a tool DL can be for agriculture. It's further worth mentioning that in (Tu et al., 2017), numerous machine learning algorithms including SVM and RFC were shown to excel in tomato disease classification as evidenced by the fact that the top performing classification technique, RFCs, came away an 89% improvement, and CNNs. According to the more recent work of (Hornyák & Iantovics, 2023), the detection of multiple maladies in tomato plant specimens was undertaken using a complex CNN architecture in an effort for it to be applicable in numerous disease scenarios, mirroring our utilization of a four-layer CNN for multi-disease classification (He et al., 2016). While CNNs have tended to dominate this sphere of research, alternative methodologies such as that of adaBoost and naïve bayes classifiers have not amassed a similar amount of attention in the realm of plant disease detection, nevertheless (Hornyák & Iantovics, 2023) provides an impressing demonstration of their effectiveness in concert with advanced feature engineering techniques for more expansive agricultural datasets. Strikingly underrepresented in academic investigations, however, remains the application of CNN for the purpose of tomato leaf disease detection. While conventional plant disease detection via CNN has been earlier looked into such as with (Brownlee, 2016) findings, tomato plants, integral to global agriculture nonetheless, has yet to be reported on in the literature, especially in following with our proposed multi-disease classification methodology.

3. Materials and Methods

This research study provides a novel tomato leaf disease classification model (CNN-ML-TLDDC) using CNN and Machine learning techniques. This section gives description of the complete methodology of suggested CNN-ML-TLDDC.

3.1 Methodology

Disease classification for tomato leaves using machine learning techniques. We describe the dataset, the CNN model architecture, data augmentation strategies, and the training and evaluation processes. Our methodology is designed to ensure that our model is efficient, and generalizable in comparison with other machine learning models. The complete CNN-ML-TLDDC model of our methodology is given in the following Figure 1.

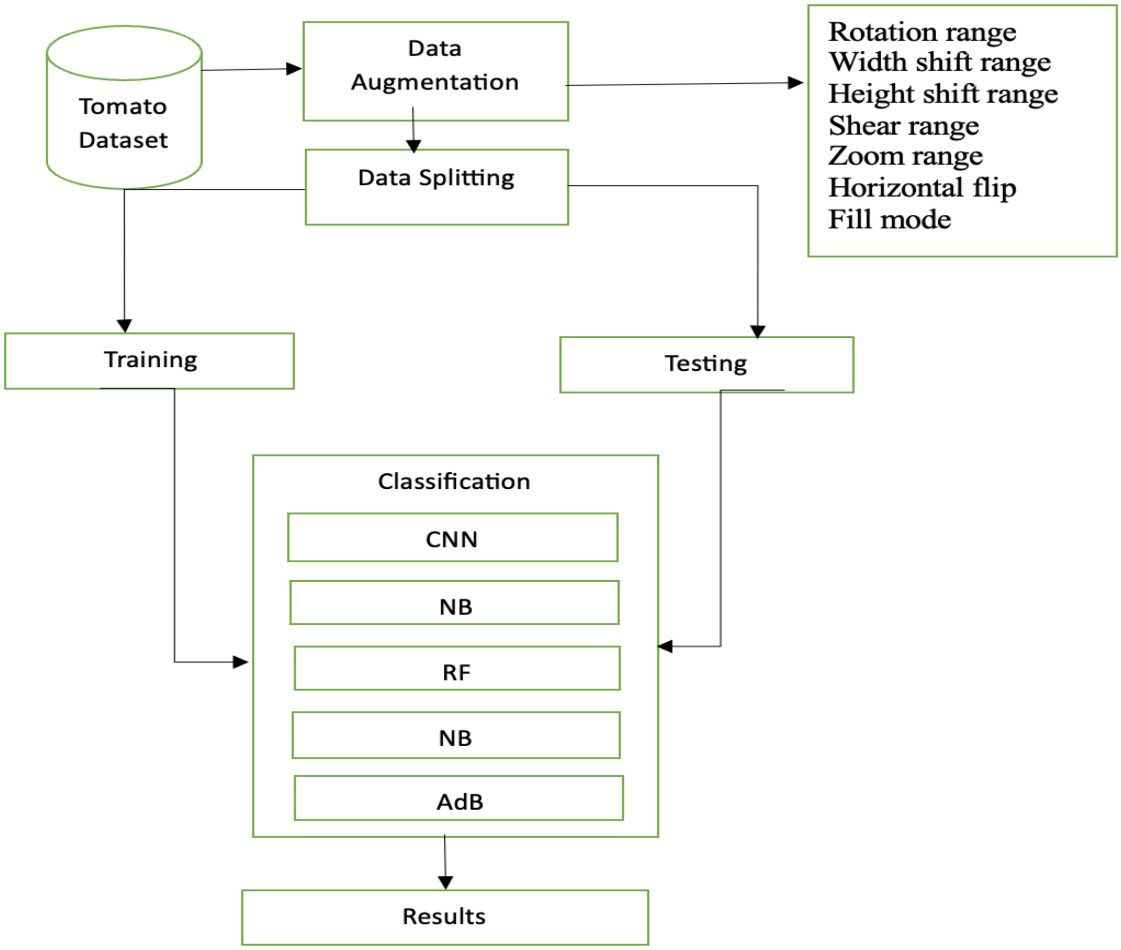

Figure 1. Methodology Diagram

3.2 Dataset

The dataset is categorized into ten said tomato leaf disease classes as indicated previously named as, BS, EB, LB, LM, SLS, TSSM, TS, MV, TYLCV, and Healthy. Each class contains images of a consistent size of 150x150 pixels. This dataset was introduced by J. Arun Pandian and Gopal Geetha Ramani.

3.3 CNN Architecture

We used the CNN, given their proven efficacy in image processing and classification tasks. The complete parameters of our given CNN architecture are presented in Figure 2.

• **Input Layer**: A 3-channel image of size 150x150 pixels.
• **Convolutional Layer 1**: 32 filters of size 3x3 with ReLU (Rectified Linear Unit) activation.
• **Max Pooling Layer 1**: Pooling size of 2x2 to down-sample feature maps.
• **Convolutional Layer 2**: 64 filters of size 3x3 with ReLU activation.
• **Max Pooling Layer 2**: Another pooling layer with a size of 2x2.
• **Convolutional Layer 3**: 128 filters of size 3x3, again with ReLU activation.
• **Max Pooling Layer 3**: 2x2 pooling size.
• **Convolutional Layer 4**: Another layer with 128 filters of 3x3 size and ReLU activation.
• **Max Pooling Layer 4**: Down-sampling with 2x2 pooling.
• **Flattening Layer**: This layer transforms the 2D matrix data to a 1D vector.
• **Fully Connected Layer (Dense Layer)**: Comprising 128 neurons with ReLU activation.
• **Dropout Layer**: A dropout rate of 0.5 to prevent overfitting.
• **Output Layer**: 10 neurons corresponding to each class, with a softmax activation function to provide a probability distribution over the classes.

Figure 2. CNN Architecture

Image classification begins with data augmentation, where we enhance our dataset through techniques like rotation, shifts, shear, zoom, and flipping.

3.4 Machine Learning Models

We also integrate traditional machine learning techniques for a comparative analysis.

NB: a probabilistic classifier known for its simplicity and efficiency in handling large datasets. We applied NB to the same dataset to assess its performance in classifying tomato leaf diseases.

RFC: different decision trees are built and ensembled for classification RFC is a very good choice to achieve high accuracy moreover it also handles unbalanced data.

KNN: it is a non-parametric classifier which is good for the datasets with closest training and offering a simple yet effective comparison point.

ABC: an ensemble technique known for improving accuracy by combining multiple weak classifiers to create a strong classifier. ABC is specifically useful in cases where data is not balanced.

3.5 Evaluation Metrics

Accuracy, precision, recall, and F1 score metrics in machine learning, are commonly used evaluation metrices, especially for problems of classification. These software characteristics provide a quantitative assessment of the performance of a classifier through comparison of its predicted outputs with the actual outputs. A confusion matrix summarizes the performance of a classification model by comparing its predicted outputs with the actual outputs through representation of the values of the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) examples in the test set. The formulas for accuracy, precision, recall:

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

4. Results

This section includes the experimental results and performance results obtained from the classifiers such as CNN, RF, NB, KNN and ABC, used on tomato leaf disease dataset.

4.1 Experiment 1

We used the number of machine learning models on tomato leaf disease dataset to classify. Also, the performance of classical machine learning algorithms like NB, RFC, KNN and ABC for tomato leaf disease classification was deployed. The Naïve Bayes model demonstrated the lowest performance, with an accuracy of 49%, precision of 46%, recall of 50%, and an F1-score of 45%. This underperformance is probably due to its posing of feature independence, which is an important limitation for handling complex, correlated patterns in image data. The Random Forest Classifier performed comparatively better, scoring 71% accuracy, 73% precision, 58% recall, and an F1-score of 58%. Regardless of its improvement over NB, the RFC's performance was still slowed down by the high-dimensional nature of the image data. The K-Nearest Neighbor algorithm demonstrated a modest performance with 56% accuracy, 57% precision, 44% recall, and an F1-score of 43%, indicating its limitations in processing complex image patterns. Similarly, the AdaBoost Classifier's performance was comparable to NB, with an accuracy of 52%, precision of 44%, recall of 43%, and an F1-score of 43%. Although ABC is known for its capability to improve classification by focusing on previously misclassified instances, it struggled with the dataset's intricate features. Detailed results, including the Confusion Matrix for each classifier and an overall performance graph, are provided in the Figure 3 and Figure 4 below:

4.2 Experiment 2

We deployed the CNN model on tomato leaf disease dataset to classify and the performance of our custom-designed CNN for the classification of tomato leaf diseases. The complexity of our CNN model is highlighted by its considerable number of trainable parameters, totaling 1,045,066. This extensive parameterization is crucial for the model's capacity to learn and differentiate subtle features within the image data. Our results were highly promising, with the model achieving remarkable precision scores across all classes (labeled 0 to 9), which ranged from 0.89 to a perfect 1.00. In terms of recall, the scores were similarly high, varying between 0.86 and 1.00, while the F1-scores spanned from 0.88 to 1.00.

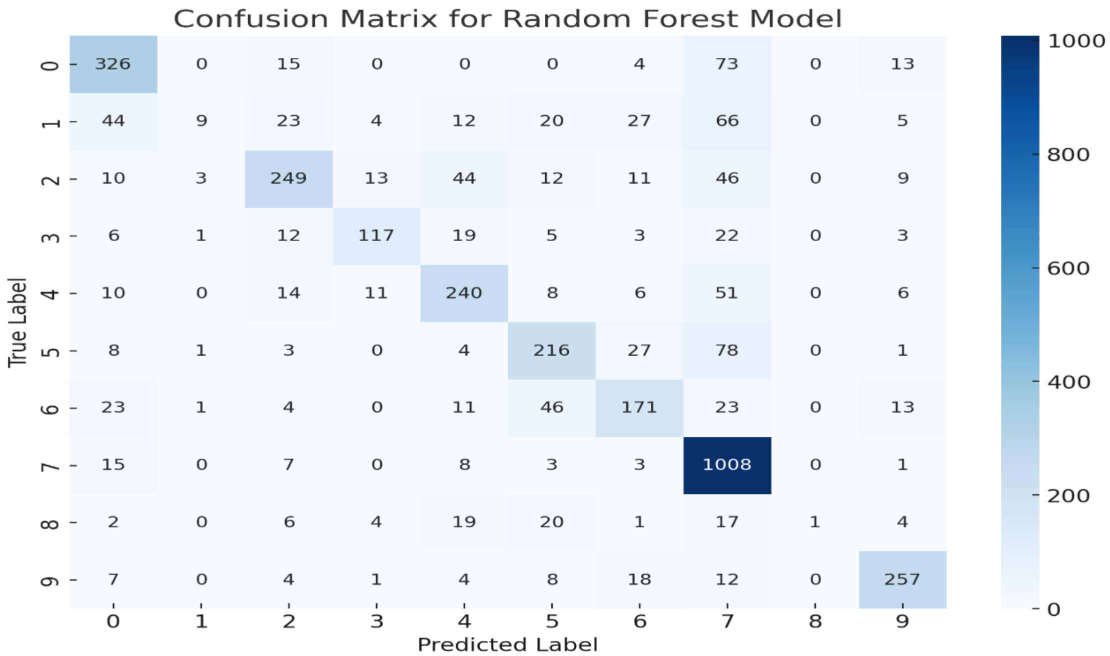

Figure 3. Confusion matrix For Random Forest Model

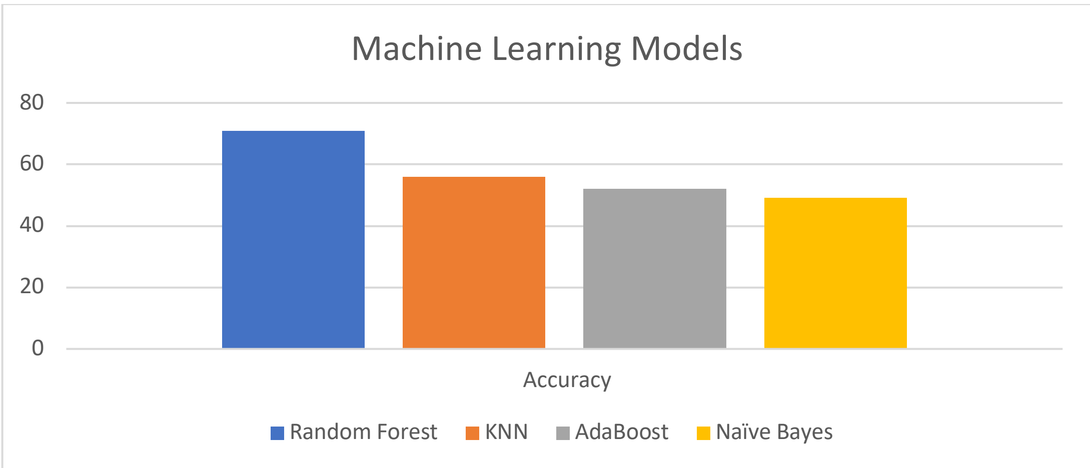

Figure 4. Accuracy graph of machine learning models

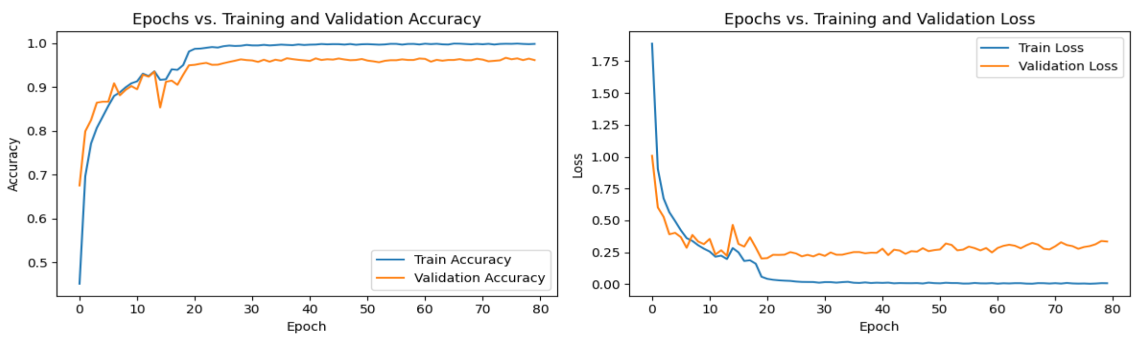

Figure 5. Training and validation accuracy loss graph

These metrics collectively signify a superior level of reliability and consistency in the model's predictive performance. A standout feature of the CNN's performance was its overall accuracy, recorded at an impressive 96%.

Furthermore, both the macro and weighted averages for key metrics such as precision, recall, and F1-score were observed to be over 0.95, underscoring the model's robustness and effectiveness in disease classification tasks. The Confusion Matrix for classifier as well as the Training and Validation accuracy chart, are provided in figure 5 and figure 6 respectively.

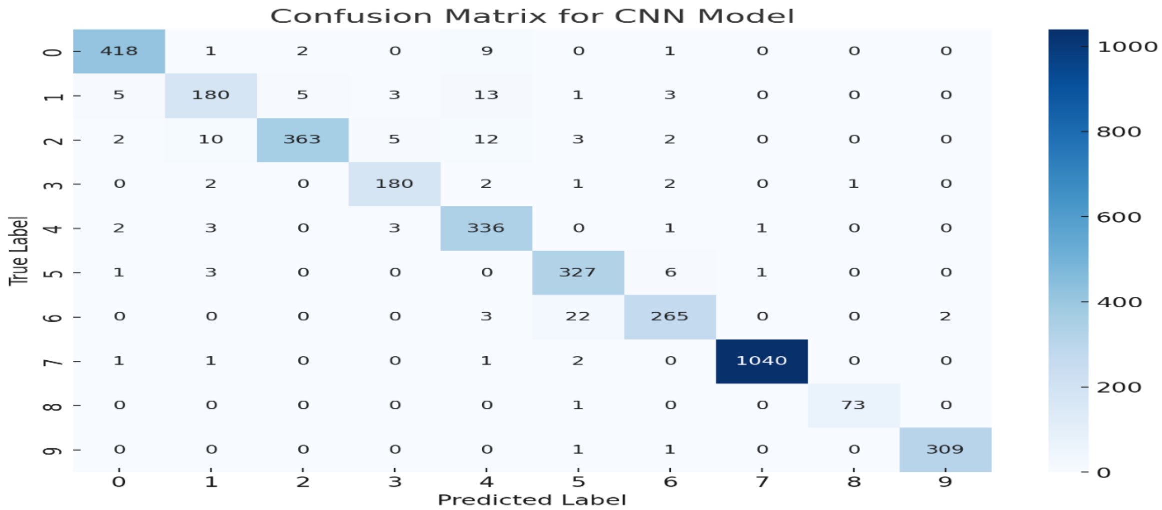

Figure 6. Confusion matrix for CNN model

5. Comparative Analysis

Now we discuss the overall performance of the deployed traditional machine learning algorithms and the CNN designated model. Convolutional Neural Networks (CNNs) in complex image classification tasks. The evaluation values of overall performance of M.L and CNN, are given in the table below:

Table 1. Evaluation Metrics of Classifiers

Model	Accuracy	Precision	Recall	F-Score
CNN	0.96	0.95	0.95	0.95
Radom Forest	0.71	0.73	0.58	0.58
Naive Bayes	0.49	0.46	0.50	0.45
k-NN	0.56	0.57	0.44	0.43
Ada-Boost	0.52	0.44	0.43	0.43

The conventional methods like Naive Bayes, Random Forest, and k-Nearest Neighbors, regardless of their general utility, demonstrate limitations while dealing with the high-dimensional and interconnected patterns usual in image data. Naive Bayes, for example, was the least efficient, mainly due to its inability to give reason for feature interdependencies. Both Random Forest and k-NN showed medium success but fell short in fully capturing the small and complex details of the image data. The AdaBoost algorithm, known for improving classification accuracy, also underperformed in this context. In total contrast, CNN displayed superior capability in managing and interpreting the multi-layered features of image data, a critical feature in detection of agricultural disease. This difference clearly shows the high proficiency of CNNs in image-based classification hurdles. Overall Performance Comparison graph of CNN and M.L classifiers is given below.

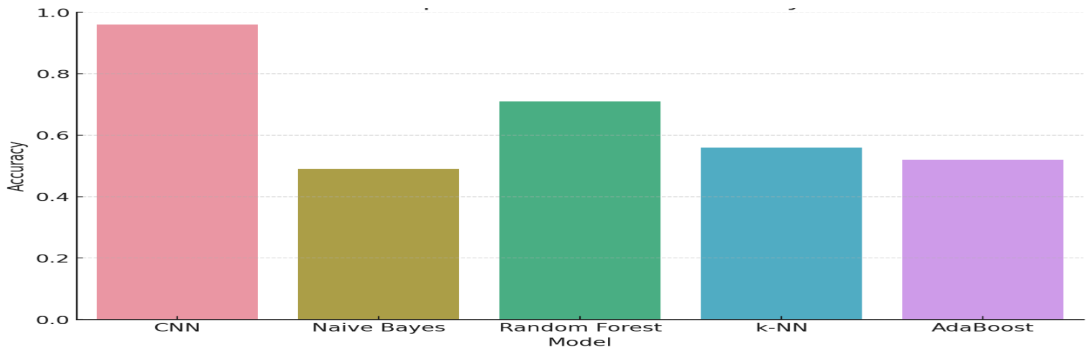

Figure 7. Overall accuracy Comparison Graph of Classifiers

6. Discussion

In this research, a Convolutional Neural Network (CNN) was developed and analyzed for image classification which tends to be a benchmark in its effectiveness against traditional machine learning algorithms such as Naive Bayes, Random Forest, k-Nearest Neighbors (k-NN), and AdaBoost. The experimental results from this study show the CNN's remarkable dominance in all key performance metrics: accuracy, precision, recall, and F1-score. The CNN's superiority lies in its competence in autonomously learning complex spatial feature hierarchies from images, a feature less available in traditional algorithms which rely on manual feature construction. This inborn strength of CNNs makes them remarkably suited for tasks that involve nuanced image data, like identifying non apparent textures and patterns. The ramifications of our findings are twofold: firstly, they stress upon the suitability of CNNs for image-based analysis; secondly, they pave way for chances for applying deep learning approaches to other intricate pattern recognition challenges across different fields i.e. from medical diagnostics to automatic navigation systems. However, it's important to acknowledge the CNN's dependence on large datasets for training which is a requirement potentially posing challenges in scenarios where the availability of data is limited.

7. Conclusions

This study tends to demonstrate the superior level of efficacy of Convolutional Neural Networks (CNNs) as compared to traditional machine learning methods such as Naive Bayes, Random Forest, k-NN, and AdaBoost in image classification tasks. The CNN's advanced capability to learn detailed feature hierarchies from image data was crucial in its high performance across accuracy, precision, recall, and F1-score metrics. This research not only emphasizes the probable ability of CNNs in complex image analysis but also suggests their application in various domains that require complex pattern recognition. The study not only highlights the strengths of CNNs but also pinpoints their dependency on elaborated datasets for training, marking an area exploration and improvement for the future.

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References

1. Andrew, J., Eunice, J., Popescu, D. E., Chowdary, M. K., & Hemanth, J. (2022). Deep Learning-Based Leaf Disease Detection in Crops Using Images for Agricultural Applications. Agronomy, 12(10). https://doi.org/10.3390/agronomy12102395
2. Brownlee, J. (2016). Master Machine Learning Algorithms Discover How They Work and Implement Them From Scratch i Master Machine Learning Algorithms. http://MachineLearningMastery.com
3. Chollet, F. (n.d.). M A N N I N G.
4. Goodfellow, I., Bengio, Y., & Courville, A. (n.d.). Deep Learning.
5. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2016-December, 770–778. https://doi.org/10.1109/CVPR.2016.90
6. Hornyák, O., & Iantovics, L. B. (2023). AdaBoost Algorithm Could Lead to Weak Results for Data with Certain Characteristics. Mathematics, 11(8). https://doi.org/10.3390/math11081801
7. James, G. (Gareth M., Witten, D., Hastie, T., & Tibshirani, R. (n.d.). An introduction to statistical learning: with applications in R.
8. Lecun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. In Nature (Vol. 521, Issue 7553, pp. 436–444). Nature Publishing Group. https://doi.org/10.1038/nature14539
9. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Müller, A., Nothman, J., Louppe, G., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, É. (2012). Scikit-learn: Machine Learning in Python. http://arxiv.org/abs/1201.0490
10. Sakkarvarthi, G., Sathianesan, G. W., Murugan, V. S., Reddy, A. J., Jayagopal, P., & Elsisi, M. (2022). Detection and Classification of Tomato Crop Disease Using Convolutional Neural Network. Electronics (Switzerland), 11(21). https://doi.org/10.3390/electronics11213618
11. Saleem, M. H., Potgieter, J., & Arif, K. M. (2020). Plant disease classification: A comparative evaluation of convolutional neural networks and deep learning optimizers. Plants, 9(10), 1–17. https://doi.org/10.3390/plants9101319
12. Simonyan, K., & Zisserman, A. (2014). Very Deep Convolutional Networks for Large-Scale Image Recognition. http://arxiv.org/abs/1409.1556
13. Sundararaman, B., Jagdev, S., & Khatri, N. (2023). Transformative Role of Artificial Intelligence in Advancing Sustainable Tomato (Solanum lycopersicum) Disease Management for Global Food Security: A Comprehensive Review. In Sustainability (Switzerland) (Vol. 15, Issue 15). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/su151511681
14. Tu, C., Liu, H., & Xu, B. (2017). AdaBoost typical Algorithm and its application research. MATEC Web of Conferences, 139. https://doi.org/10.1051/matecconf/201713900222