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Comparison of Machine Learning Algorithms in Detecting Tea Leaf Diseases

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Abstract

Tea is one of the top ten most exported products sent from Indonesia to foreign countries. However, in recent years, the amount of tea leaf exports from Indonesia has decreased, even though the export value impacts the country's economic structure. Besides market competition, Indonesia needs to maintain tea leaf production so that the spike in export decline is not significant or even increases the export production of tea leaves. To improve the quality of production and reduce production costs, early detection of tea leaf diseases is necessary. This study aims to classify tea leaf images for early detection of tea leaf disease so that appropriate treatment can be carried out early on. This study compares Machine Learning algorithms to determine the best algorithm for detecting tea leaf diseases. The algorithms tested as performance comparisons in classifying the tea leaf diseases are Random Forest (RF), Support Vector Classifier (SVC), Extra Tree Classifier (ETC), Decision Tree (DT), XGBoost Classifier (XGB) and Convolutional Neural algorithms. Network (CNN). As a result, the average accuracy performance generated by ETC produces a higher value than other algorithms, i.e., getting an average accuracy performance of 77.47%. Another algorithm, i.e., SVC, has an average accuracy of 76.57%, RF of 76.12%, DT of 65.31%, XGB of 71.62%, and the lowest is CNN of 59.08%. ETC is proven to be the most superior Machine Learning algorithm for detecting tea leaf diseases in this study.

Keywords: *comparison; machine learning; disease detection; tea leaves*

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1. Introduction

Indonesia is a tropical climate country [1] and has fertile soil for farming [2]. Farming produces food production distributed for personal consumption, sold domestically, or exported abroad. One of the highest export products from Indonesia is tea leaves, which are included in the top 10 highest export products from Indonesia [3]. In 2019, Indonesia became one of the most tea leaf exporting countries, reaching 140 thousand tons of tea leaves that were exported abroad [4]. The tea leaves produced must be found to ensure the quality is maintained [5]-[7]. In recent years, the number of tea leaf exports from Indonesia has decreased, even though the value of exports affects the country's economic structure [8]. Besides market competition, Indonesia needs to maintain the quality of tea leaves so that the surge in export decline is not significant or even increases the production of tea leaves. One cause of decreased quality of tea production is diseases of tea leaves [9], resulting in losses in production results. Tea production is often threatened by diseases that attack tea leaves, i.e., anthracnose, white spot, bird's eye, red leaf spot, brown blight, grey blight, and algal leaf [10]. Identification of tea leaves from an early age can be handled faster to minimize the distribution of tea leaves. However, 47.05% of farmers in Indonesia are lacking in conducting tea leaf nursery techniques, one of which is to identify tea leaf disease [11].

Artificial Intelligence (AI) technology is a mainstay technology for researchers to apply to various fields (e.g. health, agriculture, industry, etc.) to identify various kinds of diseases of crops [12]-[14], one of them identifies tea leaves [15]. To identify tea leaf disease, researchers usually use the derivative field of technology, i.e., Machine Learning [16]-[18]. ML is a

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derivative field of AI that focuses on producing machines by having the ability of humans to decide [19]. ML conducts learning sources by extracting data and studying the patterns given by humans. ML algorithms that are widely used by researchers, especially to detect the type of tea leaf disease, are CNN algorithms. [20], [21] With an accuracy got over 90%, Random Forest (RF) [22] with over 70% accuracy, Support Vector Classifier (SVC) [23] with over 80% accuracy, Decision Tree (DT) [24] With over 40% accuracy, and XGBoost Classifier (XGB) [24] with an accuracy of over 45%. Besides these algorithms, the authors conducted other algorithm studies used to classify images, i.e., Extra Tree Classifier (ETC) [25]. In that study, ETC produced a better model accuracy than other algorithms (DT and RF) in identifying soil cover using remote sensing, with the accuracy of the ETC model achieved over 97%. Each model has different accuracy results in classifying images. It is important to evaluate the model to choose the right algorithm and alternative algorithms in identifying the type of tea leaf disease. The selection of the right model can be done by comparing the ML algorithm, as well as Pandian et al., [26], comparing ML algorithm to classify the type of grey rot disease on tea leaves. However, the author did not find research that compares the algorithm to get the most optimal model in detecting all variants of tea leaf disease.

In short, this study aims to compare ML algorithms, i.e., RF, SVC, ETC, DT, XGB and CNN, to detect types of tea leaf disease. The novelty in this study is that researchers compare ML algorithms with a dataset containing a collection of images of all variants of tea leaf disease, i.e., anthracnose, white spot, bird's-eye, red leaf spot, brown blight, grey blight, and algal leaf. The model comparison indicator used in this study is the accuracy value, F1-Score, Recall, and Precision, as done in the study [27], in comparing the ML model to classify images.

2. Research Methods

This study aims to compare RF, SVC, ETC, DT, XGB and CNN algorithms to get the best and alternative models to detect types of tea leaf diseases. The dataset used in this study was the Tea Disease Dataset [28] with a total data of 1106 data about the picture of tea leaf disease. The selection of the best models is measured based on accuracy, precision, recall, and F1-score indicators produced by the model.

2.1 Classification of Tea Leaf Diseases

The dataset used in this study is divided into six types of tea leaf diseases, i.e., anthracnose, white spot, bird’s eye, red leaf spot, brown blight, grey blight, and algal leaf. Of the 1106 tea leaf photo data, it was divided into 2 parts, i.e., 885 were used as training data and 221 were used as testing data (70:30). Several diseases of tea leaves have almost similar characteristics, but if you look in more detail, you will see the differences. For example, red leaf spots, bird’s-eye brown blight and grey blight have the character of spots but differ in the colour of the spots. To be clearer, we present photos of tea leaves affected by the disease and their comparison with healthy tea leaves, which can be seen in Figure 1.

Figure 1. Tea Leaf Disease Data

Table 1. Factor and Characteristic Tea Leaf Diseases

Product	Description	
Antracnosis	Factor	Fungus Colletotrichum
	Characteristic	Small black circular spots on tea leaves
White Spot	Factor	Fungus Mycosphaerella
	Characteristic	The tips of the tea leaves are pale yellow and then turn white
Bird’s-eye	Factor	Helminthosporium heveae Petch
	Characteristic	The circular spots are dark red and surrounded by a dark border, like a bird's eye.
Red Leaf Spot	Factor	Pathovars of Pseudomonas syringae and Xanthomonas
	Characteristic	Irregular red or reddish brown leaf spots. When the spots coalesce, the leaves are damaged and fall off.
Brown Blight	Factor	Fungus Drechslera siccans
	Characteristic	Small brown elongated, elliptical, or necrotic spots on tea leaves
Gray Blight	Factor	Pestalotiopsis theae
	Characteristic	The brown tea leaf spots then turn to ash and spread all over the leaf
Algal Leaf	Factor	Cephaleuros virescens
	Characteristic	Circular spots or blotches, and the edges of the spots are wavy or hairy. Slowly the leaves will die if the fungus is not handled

The factors causing disease in tea leaves are environmental factors that are too humid or too dry. Besides environmental factors, other factors are pest attacks that attack tea leaves such as leaf caterpillars, mites, aphids, fungi, viruses, and bacteria. Each type of tea leaf disease has a different cause because it has different disease factors. The ML algorithm will identify photos of tea leaves affected by the disease based on the disease characteristics of the tea leaves. In Table 1, we summarize the characteristics of tea leaf disease and the factors for tea leaf disease.

2.2 System Overview

In this study, image preprocessing was performed on the photo dataset of diseased tea leaves, i.e., converting image data into array data so that the data can be studied by machines. The next stage is featuring extraction (taking object characteristics in the image) for detection. Next, we split the dataset, the best being 50% training data and 50% testing data before the modelling process is carried out using ML algorithms. An overview of the system in this study can be seen in Figure 2.

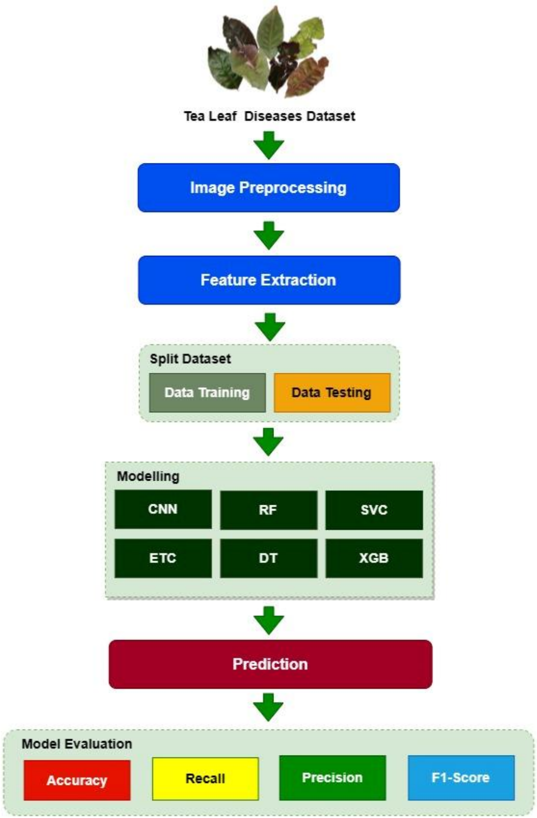

Figure 2. System Overview Comparison of Machine Learning

The ML algorithms used in this study, i.e., RF, SVC, ETC., DT, XGB and CNN, produce tea leaf disease predictions that may be different. These results are because of the sensitivity of ML models to different datasets because ML algorithms have unique patterns of learning. Model evaluation was carried out in this study to measure the best model for classifying tea leaf disease images. The evaluation used as an indicator for model measurement is accuracy, recall, precision, and F1-Score. Selection of the best model is carried out.

2.3. Random Forest (RF)

Random Forest (RF) is a classifier method that is formed from decision trees and random selection features [29]. To produce disease predictions on tea leaves using RF, sci-kit-learn (python module) performs the most voting of all decision trees. Each decision tree (*hx*) produces predictions of tea leaf disease. Each decision tree is calculated using Gini Importance, which is a binary tree that has two nodes. The calculation of Gini Importance can be seen in Formula 1.

$$ni_j = w_{left(j)}c_{left(j)} - w_{right(j)}c_{right(j)} \quad (1)$$

ni_j is node *j*, $w_{left(j)}$ and $w_{right(j)}$ are the number of samples that reach node *j* from the left and right nodes, $c_{left(j)}$ and $c_{right(j)}$ are the impurity values of node *j* from the left and right nodes. Furthermore, the significant value in each decision tree can be calculated using Formula 2.

$$fi_i = \frac{\sum j{:}node\ j\ splits\ on\ feature\ i\ ni_j}{\sum k \in all\ nodes\ ni_k} \quad (2)$$

fi is the important feature *i*, and *ni* is the important node *j*. Furthermore, the result is normalized to a value between 0 and 1 divided by the sum of all the feature importance values ($normfi_i$). To calculate it can be seen in Formula 3.

$$normfi_i = \frac{fi_i}{\sum j \in all\ features\ fi_j} \quad (3)$$

The last step calculates the average across all trees with the total value of important features in each tree ($normfi_{ij}$) divided by the number of trees (*T*). RF calculations can be seen in Formula 4.

$$RF = \frac{\sum j \in all\ trees\ normfi_{ij}}{T} \quad (4)$$

2.4 Support Vector Classifier (SVC)

The Support Vector Classifier (SVC) in the detection of tea disease in this study classifies data by entering the kernel, which aims to find a hyperline (separator) to provide the maximum margin distance between classes. Figure 3 is an illustration of seven classes and hyperlines formed using SVC.

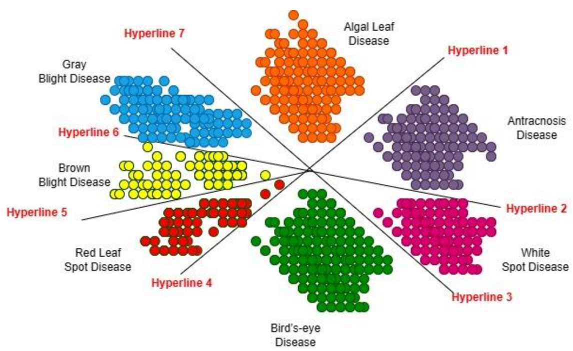

Figure 3. Illustration of SVC classifying diseased tea leaves

It is necessary to select the right kernel to produce a good hyperline so that the model produces optimal predictions of tea disease. In this study, seven classes of tea leaf diseases are formed, resulting in seven hyperlines. To calculate hyperline can be seen in Formula 5.

$$w \cdot x_i + b = 0 \quad (5)$$

In Formula 5, *w* describes the model parameters, *x* describes the attribute values and *b* describes the scalars used as tea leaf disease bias.

2.5 Extra Tree Classifier (ETC)

Extra Tree Classifier (ETC) ETC studies tea leaf disease datasets with a highly randomized tree structure, similar to RF. Each ETC decision tree is formed from image training data of diseased tea leaves and is tested using a random sample that has k-features to get the best prediction and accuracy value. To implement ETC in classifying tea leaf disease images, the first step is to calculate the entropy value. Entropy is the homogeneity value of class distribution in a collection of objects. The entropy value got is proportional to the homogeneity of the class distribution in the tea leaf image. To get the Entropy value in a decision tree, you can use Formula 6.

$$Entropy\ (S) = \sum_{i=1}^{0} P_i \log 2^{P_i} \quad (6)$$

The sample subset is represented by P_i and *i* represents an attribute value. The next step is to make a feature selection that shows random variable knowledge. The higher the feature selection value (Gain) gets the better ETC produces predictions. To get the Gain value, use the following Formula 7.

$$Gain(S, A) = \sum_{v \in V(A)} \frac{|S_v|}{|S|} Entropy(S_v) \quad (7)$$

2.6 Decision Tree (DT)

Decision Tree (DT) is a classifier algorithm that organizes each option into a branching node [30]. DT has a tree-like structure that has branches, roots, and leaves.

2.7 XGBoost Classifier (XGB)

Extreme Gradient Boosting (XGB) is an ML algorithm that combines gradient descent and boosting, which is usually called Gradient Boosting Classifier [31]. Boosting is an ensemble learning algorithm that gives different weights for training data distribution for each iteration. Each boosting iteration adds weight for the miss-classified error sample and subtracts weight for the correct-classified sample, so it changes the training data distribution effectively.

2.8 Convolutional Neural Algorithms. Network (CNN)

Convolutional Neural algorithms. Network (CNN) is an algorithm developed from the Multilayer Perception which functions to process two-dimensional data and belongs to the Deep Learning (DL) section [32]. DL is a subset of ML that learns by understanding patterns based on large data and complex variables. CNN has three-dimensional layers (width, height, and depth) and has neurons in each layer that are interconnected. Figure 4 is an example of the application of CNN in detecting tea leaf disease and the results got are that the tea leaves are detected by Brown Blight disease.

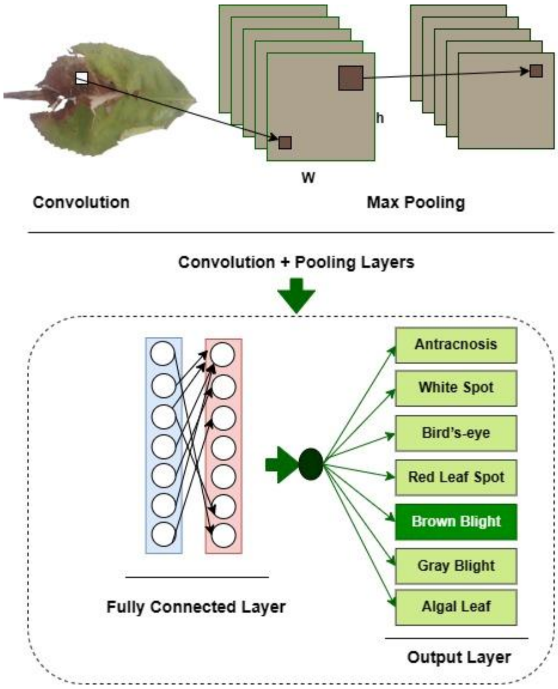

Figure 4. Illustration of SVC classifying diseased tea leaves

In our case study, images of diseased tea leaves pass through a series of convolution layers and converge to maximum values in the alternative modes. Use Formula 8 to form a series of convolutions.

$$z^l = h^{l-1} \times W^l \quad (8)$$

h is the layer height and *W* is the layer width. When the diseased leaf images have been convoluted, a feature map is created and inserted into the Max Pooling layer. Max Pooling is to return the maximum value of the image section in the kernel. The next step is to integrate the maximum value into the feature mapping and transform it into a vector through the weight matrix. At this stage, all possibilities are connected with neurons and produce output from the output vector.

2.9 Evaluation Matrix

Evaluation of performing the ML algorithms in identifying tea leaf diseases used in this study was accuracy, precision, recall, and F1-Score. The accuracy of the model shows the percentage of accuracy of the prediction results which are predicted to be correct according to the actual type of tea leaf disease. The precision of the model shows the accuracy of the positive prediction results of tea leaf disease, which are correctly predicted compared to the total data that are classified as positive for diseased tea leaves. If the precision is compared to the total data that is classified as positive for diseased tea leaves, on recall the positive prediction is compared to all data that is positive for disease in the testing data. To get an average comparison between precision and recall, you can calculate the F1-Score value. To calculate the values for accuracy, precision, recall, and F1-Score, it is necessary to get data values that predict correctly and incorrectly. We present a matrix evaluation image as an illustration of the prediction data grouping, which can be seen in Figure 5.

	Antracnosis	White Spot	Bird's-eye	Red Leaf Spot	Brown Blight	Gray Blight	Algal Leaf
Antracnosis	TA	FA	FA	FA	FA	FA	FA
White Spot	FWS	TWS	FWS	FWS	FWS	FWS	FWS
Bird's-eye	FBE	FBE	TBE	FBE	FBE	FBE	FBE
Red Leaf Spot	FRLS	FRLS	FRLS	TRLS	FRLS	FRLS	FRLS
Brown Blight	FBB	FBB	FBB	FBB	TBB	FBB	FBB
Gray Blight	FGB	FGB	FGB	FGB	FGB	TGB	FGB
Algal Leaf	FAL	FAL	FAL	FAL	FAL	FAL	TAL

Figure 5. Illustration of tea leaf disease prediction matrix evaluation

In Figure 5, the prediction results for diseased leaves are marked in green with details: (1) TA is True Positive Anthracnosis, and FA is False Positive Anthracnosis, (2) TWS is True Positive White Spot and FWS is False Positive White Spot, (3) TBE is True Positive Bird's-eye and FBE is False Positive Bird's-eye, (4) TRLS is True Positive Red Leaf Spot and FRLS is False Positive Red Leaf Spot, (5) TBB is True Positive Brown Blight and FBB is False Positive Brown Blight, (6) TGB is True Positive Gray Blight and FGB is False Positive Gray Blight, (7) TAL is True Positive Algal Leaf and FAL is False Positive Algal Leaf.

True Positive (TP) shows that the system predicts correctly that the leaves are diseased in that class, and False Positive (FP) shows that the system predicts false positive which means the system detects diseased tea leaves in a certain class, but the actual data is that the tea leaves are diseased in other classes or even not diseased.

The True Negative (TN) class is a collection of images that are correctly predicted that the tea leaves are not a disease in that class, but are diseased in another class. Then False Negative (FN) is a collection of images that are predicted not to be a disease in that class, but the actual data for the image is a disease in that class. In summary, the calculation of accuracy, precision, recall, and the F1-Score model can be seen in Formulas 9 through 12.

$$Accuracy = \frac{\sum TN + \sum TP}{\sum TP + \sum TN + \sum FP + \sum FN} \tag{9}$$

$$Precision = \frac{\sum TP}{\sum TP + \sum FP} \tag{10}$$

$$Recall = \frac{\sum TP}{\sum TP + \sum FN} \tag{11}$$

$$F1 - Score = 2 \times \frac{Recall + Precision}{Recall \times Precision} \tag{12}$$

According to F. Gorunescu in a paper compiled by Agustina, et al. [33] the model evaluation results are categorized as very good if you get a score of 90% to 100%, a good category with a value of 80% to 90%, well with a value of 70% to 80%, bad with a value of 60% to 70%, and produce machine errors with accuracy values below 60%.

3. Results and Discussions

The predictions generated by each algorithm in detecting the type of tea leaf disease were that we got different values of accuracy, precision, recall, and F1-Score. ETC, SVC, RF, and XGB algorithm has a fairly good model sensitivity to the Tea Disease Dataset with a model accuracy of over 70%. These results prove these algorithms are quite good at detecting types of tea diseases and further research can be carried out. Our goal, i.e., to compare the ML algorithms (RF, SVC, ETC, DT, XGB and CNN) to detect the type of tea leaf disease we summarize in this section.

The results of our analysis in this study are that the ETC algorithm is the most sensitive algorithm for the Tea Disease Dataset. The sensitivity of ETC, RF, and SVC is proven in these results to have a fairly good sensitivity to the tea leaf disease dataset. Other algorithms can be used as alternatives with quite good algorithm categories, i.e., the XGB algorithm with a model accuracy of 71.62%.

In this study, the DT algorithm is included in the category of algorithms that have poor sensitivity to the tea leaf disease dataset, because it only gets an accuracy value of 65.32%. The CNN algorithm is detected to be very insensitive to the tea disease dataset because it only gets an accuracy of 59.08%.

The results of the analysis are based on the accuracy value obtained by the ETC algorithm which is greater than the other algorithms The performance of the ML algorithms that we have measured can be seen in Figure 6.

In Figure 6, several algorithms produce accuracy values that are not much different, i.e., RF accuracy which is only 1.35% different and SVC which is only 0.57% different from the highest algorithm accuracy, i.e., ETC which gets the highest accuracy of 77.48% compared to other algorithms.

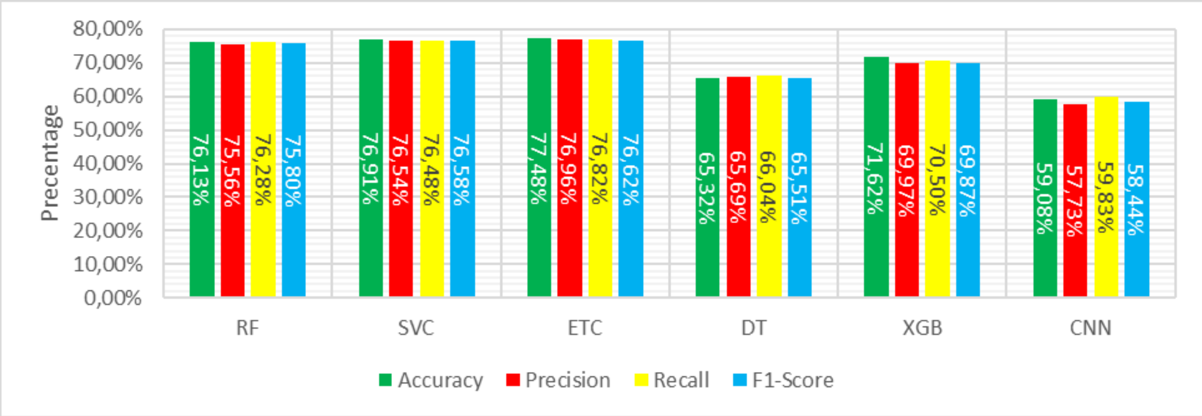

Figure 6. Comparison of Algorithms in Detecting Types of Diseases of Tea Leaves

The priority in research on disease detection in tea leaves is to identify tea leaves that are positive for the disease compared with tea leaves that are negative but detected positive. Therefore, the recall indicator is also taken into consideration in the evaluation of the ML model conducted in this study. In this study, the recall showed that there were many positive cases of diseased leaves that had diseased tea leaves. The higher the recall value, showing the percentage of positive cases of diseased leaves carried out by the model on the actual data, the more accurate it is. In this study, the ETC algorithm was the best in detecting positive cases of diseased leaves with a recall value of 76.82%. Other algorithms also get quite good recall values, i.e., recall values of 76.48% for SVC, 76.28% for RF, and 70.50% for XGB. DT and CNN are bad both in detecting positive cases of diseased leaves, with a model accuracy below 70%.

Furthermore, precision indicators are usually used to measure the sensitivity of models with positive error priority. In our study, cases of false positives (eg detected a diseased leaf but a non-disease tea leaf) were not prioritized. However, considering that it is not a problem to treat tea leaves that are not diseased, it can be a way to prevent tea leaf disease. We make our precision value one of the measurement indicators. In this case, ETC, SVC, and RF are good algorithms for detecting false positives with an accuracy of more than 70%. Other algorithms, i.e., DT, XGB, and CNN are quite bad at detecting false positives for tea leaf disease with a precision value of less than 70%.

The F1-Score measures the harmonic average between recall and precision. Due to the priority bias between recall and precision, we consider measuring the F1-Score. The best F1-Score value is ETC with a value of 76.62%, followed by SVC of 76.58% and RF of 75.80%. The DT, XGB, and CNN algorithms are not good at producing harmonic averages with F1-Score values obtained below 70%.

Finally, the DT algorithm has poor sensitivity to the tea leaf disease dataset of all the indicators we evaluate. The CNN algorithm was unsuccessful in classifying the tea leaf disease as evidenced by the low scores on all indicators, the ETC Algorithm being the recommended algorithm to be used as a model for detecting tea leaf types, with other alternative algorithms being RF, SVC, and XGB because they have low values. Quite far from the values generated by ETC on all the indicators we evaluated.

4. Conclusions

The results of the analysis of the ML model to detect tea leaf disease are divided into seven, i.e., anthracnose, white spot, bird's-eye, red leaf spot, brown blight, grey blight, and algal leaf. In this study, we compared ML classifier algorithms to detect leaf disease using the Tea Disease Dataset. ETC produces the highest score on all indicators (accuracy, precision, recall, and F1-Score) with each value above 70% and belongs to the model category, which is quite good at classifying images. However, we get alternative algorithms with good categories on all indicators, i.e., the RF and SVC algorithms. XGB has a value above 70% on the resulting accuracy and recall, but on the precision indicator and F1-Score, it gets a value below 70%. In XGB, not all indicators get good categories, so that it can be used as an in-depth consideration for future research. The other two algorithms, i.e., DT and CNN, are in a bad category because they get scores below 70% on all indicators.

For future research, we suggest improving the XGB, DT and CNN algorithms to improve model performance in detecting tea leaf diseases. For example, by implementing ensemble methods to improve better performance when collaborating on model algorithms.

References

[1] S. Salsabila, I. Rahmiyani, and D. Sri Zustika, "Nilai Sun Protection Factor (SPF) pada Sediaan Lotion Ekstrak Etanol Daun Jambu Air (Syzygium aqueum)," Majalah Farmasetika,

vol. 6, no. Suppl 1, p. 123, 2021, doi: 10.24198/mfarmasetika.v6i0.36664.

[2] Q. Ayun, S. Kurniawan, and W. A. Saputro, "Perkembangan Konversi Lahan Pertanian Di Bagian Negara Agraris," Vigor: Jurnal Ilmu Pertanian Tropika Dan Subtropika, vol. 5, no. 2, pp. 38–44, 2020, doi: 10.31002/vigor.v5i2.3040.

[3] Subdirektorat Statistik Ekspor, Buletin Statistik Perdagangan Luar Negeri, Desember. Jakarta: BPS RI, 2020.

[4] H. Nursodik, S. Imam Santoso, and S. Nurfadillah, "Competitiveness of Indonesian Tea Export in Southeast Asia Markets," SOCA: Jurnal Sosial, Ekonomi Pertanian, vol. 16, no. 1, p. 1, 2022, doi: 10.24843/soca.2022.v16.i01.p01.

[5] Y. Sari and S. W. Meisari, "Alat Penyortir Warna Daun Teh Menggunakan Sensor Tcs3200 Berbasis Raspberry Pi Dan Arduino," Tekinfo, vol. 22, no. 1, pp. 117–130, 2021.

[6] M. I. Sadikin, T. Swandari, and F. Wilisiani, "Membangun Sinergi antar Perguruan Tinggi dan Industri Pertanian dalam Rangka Implementasi Merdeka Belajar Kampus Merdeka," Seminar Nasional dalam Rangka Dies Natalis ke-45 UNS Tahun 2021, vol. 5, no. 1, pp. 245–252, 2021.

[7] M. I. Prawira-Atmaja et al., "Evaluasi Kesesuaian Mutu Produk Teh Dengan Persyaratan Standar Nasional Indonesia," Jurnal Standardisasi, vol. 23, no. 1, p. 43, 2021, doi: 10.31153/js.v23i1.845.

[8] S. D. S. T. Perkebunan, STATISTIK TEH INDONESIA 2021, no. 1. Jakarta: BPS RI, 2021.

[9] L. Q. Aini, "Efektivitas Tribasik Tembaga Sulfate (93%) Terhadap Penyakit Cacar Daun Exobasidium vexans Pada Tanaman Teh," Jurnal Sumberdaya Alam dan Lingkungan, vol. 9, no. 2, pp. 76–81, 2022, doi: 10.21776/ub.jsal.2022.009.02.5.

[10] J. Chen, Q. Liu, and L. Gao, "Visual tea leaf disease recognition using a convolutional neural network model," Symmetry, vol. 11, no. 3, 2019, doi: 10.3390/sym11030343.

[11] Saeful Rahmat, "Pengaruh Pemberdayaan Petani Terhadap Penerapan Teknologi Budidaya Serta Implikasinya Pada Produktivitas Kebun Teh Rakyat (Camellia sinensis)," Repository Universitas Winaya Mukti, 2020.

[12] H. Orchi, M. Sadik, and M. Khaldoun, "On using artificial intelligence and the internet of things for crop disease detection: A contemporary survey," Agriculture (Switzerland), vol. 12, no. 1, 2022, doi: 10.3390/agriculture12010009.

[13] A. V. Panchal, S. C. Patel, K. Bagyalakshmi, P. Kumar, I. R. Khan, and M. Soni, "Image-based Plant Diseases Detection using Deep Learning," Materials Today: Proceedings, no. September, 2022, doi: 10.1016/j.matpr.2021.07.281.

[14] T. Domingues, T. Brandão, and J. C. Ferreira, "Machine Learning for Detection and Prediction of Crop Diseases and Pests: A Comprehensive Survey," Agriculture (Switzerland), vol. 12, no. 9, pp. 1–23, 2022, doi: 10.3390/agriculture12091350.

[15] W. Wu, "Identification of tea leaf diseases based on deep transfer learning," vol. 2, no. 3, pp. 3–5, 2022.

[16] J. Chen and J. Jia, "Automatic Recognition of Tea Diseases Based on Deep Learning," in Advances in Forest Management under Global Change, vol. 11, no. tourism, IntechOpen, 2020, p. 13. doi: 10.5772/intechopen.91953.

[17] G. Hu, H. Wang, Y. Zhang, and M. Wan, "Detection and severity analysis of tea leaf blight based on deep learning," Computers & Electrical Engineering, vol. 90, p. 107023, Mar. 2021, doi: 10.1016/j.compeleceng.2021.107023.

[18] G. Hu, X. Yang, Y. Zhang, and M. Wan, "Identification of tea leaf diseases by using an improved deep convolutional neural network," Sustainable Computing: Informatics and Systems, vol. 24, p. 100353, Dec. 2019, doi: 10.1016/j.suscom.2019.100353.

[19] G. Volkmar, P. M. Fischer, and S. Reinecke, "Artificial Intelligence and Machine Learning: Exploring drivers, barriers, and future developments in marketing management," Journal of Business Research, vol. 149, no. April 2021, pp. 599–614, 2022, doi: 10.1016/j.jbusres.2022.04.007.

[20] W. Bao, T. Fan, G. Hu, D. Liang, and H. Li, "Detection and identification of tea leaf diseases based on AX-RetinaNet," Sci Rep, vol. 12, no. 1, pp. 1–16, 2022, doi: 10.1038/s41598-022-06181-z.

[21] M. G. Lanjewar and K. G. Panchbhai, "Convolutional neural network based tea leaf disease prediction system on smartphone using paas cloud," Neural Comput Appl, vol. 35, no. 3, pp. 2755–2771, Jan. 2023, doi: 10.1007/s00521-022-07743-y.

[22] X. Zou, Q. Ren, H. Cao, Y. Qian, and S. Zhang, "Identification of tea diseases based on spectral reflectance and machine learning," Journal of Information Processing Systems, vol. 16, no. 2, pp. 435–446, 2020, doi: 10.3745/JIPS.02.0133.

[23] S. Mukhopadhyay, M. Paul, R. Pal, and D. De, "Tea leaf disease detection using multi-objective image segmentation," Multimedia Tools and Applications, vol. 80, no. 1, pp. 753–771, Jan. 2021, doi: 10.1007/s11042-020-09567-1.

[24] S. Meng, S. Wang, T. Zhou, and J. Shen, "Identification of Tea Red Leaf Spot and Tea Red Scab Based on Hybrid Feature Optimization," Journal of Physics: Conference Series, vol. 1486, no. 5, 2020, doi: 10.1088/1742-6596/1486/5/052023.

[25] A. I. Champa, Md. F. Rabbi, S. M. Mahedy Hasan, A. Zaman, and Md. H. Kabir, "Tree-Based Classifier for Hyperspectral Image Classification via Hybrid Technique of Feature Reduction," in 2021 International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD), IEEE, Feb. 2021, pp. 115–119. doi: 10.1109/ICICT4SD50815.2021.9396809.

[26] J. A. Pandian, S. N. Nisha, K. Kanchanadevi, A. K. Pandey, and S. K. Rima, "Grey Blight Disease Detection on Tea Leaves Using Improved Deep Convolutional Neural Network," Computational Intelligence and Neuroscience, vol. 2023, pp. 1–11, 2023, doi: 10.1155/2023/7876302.

[27] R. T. Tedjo, A. M. Sambul, and A. S. M. Lumenta, "Klasifikasi Gambar Bahan Makanan untuk Penderita Buta Warna," Jurnal Teknik Elektro dan Komputer, vol. 11, no. 2, p. 67, 2022, doi: 10.35793/jtek.11.2.2022.37794.

[28] G. Kimutai and A. Förster, "tea sickness dataset." Mendeley Data, p. https://data.mendeley.com/datasets/j32xdt2ff5, 2022. doi: 10.17632/j32xdt2ff5.2.

[29] H. Pramoedyo, D. Ariyanto, and N. N. Aini, "Comparison of Random Forest and Naïve Bayes Methods for Classifying and Forecasting Soil Texture in the Area Around Das Kalikonto, East Java," BAREKENG: Jurnal Ilmu Matematika dan Terapan, vol. 16, no. 4, pp. 1411–1422, 2022, doi: 10.30598/barekengvol16iss4pp1411-1422.

[30] A. Surya, "Machine Learning and Ensemble Approach Onto Predicting Heart Disease," pp. 1–7, Nov. 2021.

[31] suwarno and R. Kusnadi, "Analisis Perbandingan SVM, XGBoost dan Neural Network pada Klasifikasi," Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi), vol. 5, no. 5, pp. 896–903, Oct. 2021, doi: 10.29207/resti.v5i5.3506.

[32] C. N. Ihsan, "Klasifikasi Data Radar Menggunakan Algoritma Convolutional Neural Network (CNN)," DoubleClick: Journal of Computer and Information Technology, vol. 4, no. 2, p. 115, 2021, doi: 10.25273/doubleclick.v4i2.8188.

[33] N. Agustina, Adrian, and M. Hermawati, "Implementasi Algoritma Naïve Bayes Classifier untuk Mendeteksi Berita Palsu pada Sosial Media," vol. 14, no. 4, pp. 1979–276, 2021, doi: 10.30998/faktorexacta.v14i4.11259.