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Integration of Deep Learning for Optimization of Coconut Farming in North Sulawesi through Disease Detection Based on Hybrid CNN and LSTM Approaches

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ABSTRACT

This research aims to develop a palm leaf disease detection system based on a Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) integrated into a mobile application. The CNN model is used to extract visual features from leaf images, while the BiLSTM serves to capture sequential dependencies, thereby improving classification accuracy. The implementation was carried out by connecting the model, which is served via a Flask API, and accessed by the mobile application using Ngrok as a tunneling service for testing. Test results show that the system is capable of detecting healthy leaf conditions with an accuracy rate of up to 99.7%, and provides descriptive information about the leaf's condition and preventive treatment recommendations. The integration of the model into a mobile application enables real-time plant health monitoring, making it an innovative solution to support farmers in increasing productivity and preventing losses due to disease outbreaks.

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I. INTRODUCTION

Indonesia is the world's largest producer of coconuts, with over 5.6 million farming households managing coconut plantations, accounting for approximately 34% of global coconut farmers. According to the national coconut downstreaming roadmap, North Sulawesi and Riau are recorded as the provinces with the largest coconut plantation areas in Indonesia. Specifically, North Sulawesi has the largest state-owned plantation, covering 0.08% of the total coconut plantation area in the region. This is supported by two main research locations: the Paniki Experimental Farm (100 ha) and the Pandu Experimental Farm (80 ha), managed by BRIN and the local BPTP. Based on 2023. However, the Ministry of Agriculture recorded a decline in national coconut production in 2024, dropping by 70.55 million nuts to 14.11 billion nuts. Coconut farmers in North Sulawesi have suffered losses of up to billions of rupiah in recent years [1].

This decline in productivity is largely attributed to attacks by various plant diseases such as Caterpillars, Leaflets, Drying of Leaflets, Flaccidity, and Yellowing [2]. Field data reveal that conventional diagnostic methods, which rely on visual observation, have a high error rate [3]–[6], particularly in the early stages of infection [7]–[9]. These diagnostic errors have fatal consequences, as the control measures taken are often misdirected [10]-[11], leading not only to wasted time and costs but also potentially causing pathogen resistance [12]–[17]. A survey of coconut farmers in North Sulawesi showed that most lack sufficient knowledge to accurately distinguish symptoms of coconut diseases, exacerbating the problem.

Amid these challenges, advancements in deep learning technology offer a potential solution through a hybrid approach combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM). While CNN excels at extracting visual features from plant leaves [18], it has limitations in understanding the temporal context of disease progression, as it only analyzes static images. This weakness makes CNN prone to diagnostic errors when faced with temporary variations due to environmental factors or unclear early-stage infections [19]. This is where LSTM plays a crucial role, with its ability to process sequential data, allowing the system to track disease progression, distinguish daily fluctuations from actual infection trends, and predict potential symptom development in the future [20].

The hybrid CNN-LSTM integration offers a comprehensive solution by combining CNN's strengths in spatial analysis with LSTM's capabilities in temporal processing [21], [22]. This approach is highly relevant for addressing the characteristics of coconut diseases in North Sulawesi, which have both spatial (visual symptoms on leaves) and temporal (symptom progression over time) aspects. This hybrid system is expected to create a disease detection tool that is not only accurate in identifying current visual symptoms but also understands the context of disease dynamics holistically. Thus, this research aims to develop a practical deep learning-based technological solution to support the optimization of coconut farming in North Sulawesi through a more reliable and comprehensive disease detection system..

II. METHODOLOGY

The proposed research implementation method uses the Cross-Industry Standard Process for Data Mining (CRISP-DM). This framework is a widely recognized standard methodology that can be broadly applied in the data mining process [23]. Based on this method, the author has formulated the research flow shown in Figure 1.

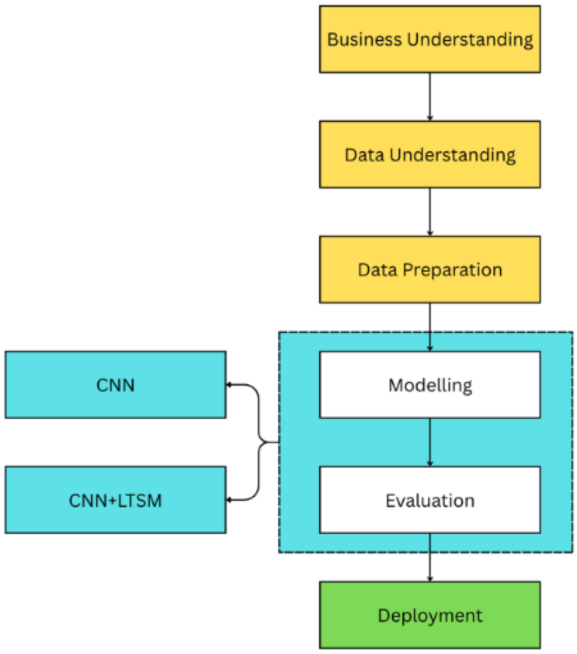

Fig. 1. Methodology

A. Business Understanding

A literature study was conducted by exploring and understanding relevant research from credible sources. This was done to gain a clear understanding of previously conducted studies, so that they can be developed and applied in the stages of the current research.

B. Data Understanding

After the business process is identified, the next step is to examine the data that will be used. The data used consists of images of coconut plants.

Fig. 2. Dataset example: left - coconut leaf positive for caterpillar disease, right - coconut leaf positive for flaccidity disease.

C. Data Preparation

This stage is the process of adjusting the dataset before the modeling phase. In this stage, the entire dataset will be processed and standardized to align with each other as needed. To validate the obtained dataset, consultations will be conducted regarding the dataset's validity with experts, in this case, lecturers and/or researchers from the relevant field.

D. Modelling

After all data has undergone the collection and processing stages, the modeling phase will be carried out to identify the dataset. The modeling process requires a large dataset to create a credible model for subsequent testing.

E. Evaluation

Evaluation is conducted through a series of model testing and validation scenarios using the obtained data. One of the scenarios to be implemented in this research is combining the CNN algorithm with LSTM to improve assessment accuracy. Further evaluation will compare the combined CNN and LSTM approach with processing using CNN.

F. Deployment

The deployment process is carried out after the model has been tested with various prepared scenarios and is declared ready for use in the image detection process.

III. RESULT AND DISCUSSION

The obtained data is divided into 6 categories, presented in more detail in Table 1.

TABLE 1. DATASET DIVISION

No	*Leaf Condition*	*Quantity*
1	Caterpillars	990
2	Leaflet	795
3	Healthy	123
4	Dryingofleaflets	1,078
5	flaccidity	1,069
6	yellowing	1,084
	Quantity	5,139

The data above was obtained by collecting data from several coconut plantation locations in North Sulawesi and from the North Sulawesi Experimental Garden Office. After the data is categorized, it will enter the data preprocessing stage. The modeling/training phase is conducted using two approaches: first, a CNN algorithm combined with LSTM, and second, using CNN alone. This is done to obtain a comparison and determine whether the Hybrid CNN-LSTM approach yields an improvement in accuracy or not.

Data Preparation

Data preparation is carried out in 3 stages. The first is resizing to 128 x 128 pixels, which aims to standardize the format of all dataset files. After the resizing process, a gridding process is performed. In CNN, the process involves feature extraction from the image (spatial), while LSTM is used to understand sequences. Therefore, the existing data needs to undergo gridding, which divides one data point into 4 x 4 sections (grids). This allows LSTM to read the gridded photos. However, the output of the 4 x 4 gridding process is still not readable by LSTM, so a labeling process for the gridding results is necessary. This enables LSTM to process the data according to the sequence of labels.

Modelling

The Convolutional Neural Network (CNN) model used in this research is designed with a layered architecture. The network structure consists of two main convolutional blocks, each followed by a max-pooling layer, enabling it to extract important spatial features from the images while reducing data dimensions for computational efficiency. After the feature extraction process, the results are flattened through a flattening layer and passed to a dense layer to form a more comprehensive representation. To reduce the risk of overfitting, a dropout layer is also added, allowing the model to learn in a more generalized manner.

This model is compiled using the Adam optimizer, which is known for its effectiveness in accelerating training convergence, and utilizes the categorical crossentropy loss function as the data is multi-class. The primary metric used is accuracy, in line with the image classification objective. The final result is a trained model saved in .h5 format, which allows the model to be easily reloaded for evaluation or further implementation needs. This architectural design was chosen for its simplicity and proven effectiveness in recognizing visual patterns within the coconut image dataset..

Fig. 3. Confusion Matrix CNN

The confusion matrix in Figure 3 illustrates the model's performance in classifying the six classes of coconut leaf images. The majority of the test data were correctly mapped, as indicated by the dominant values along the main diagonal. For example, the CCI_Caterpillars class had 198 samples accurately identified. Misclassifications were relatively minor and generally occurred between classes with visual similarities. Therefore, the model is considered reasonably effective, though improvements are still needed for specific classes.

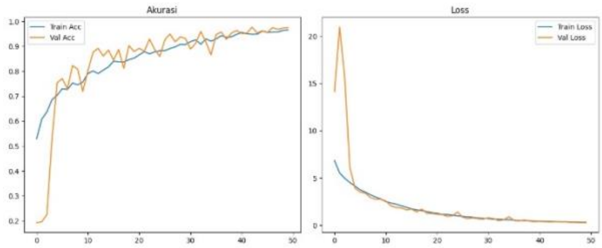

Fig. 4. CNN model accuracy graph

Figure 4 shows a steady increase in accuracy, exceeding 90% for both training and validation data. The loss curve also decreases consistently with a similar pattern for both datasets, indicating that the model is learning optimally without signs of overfitting.

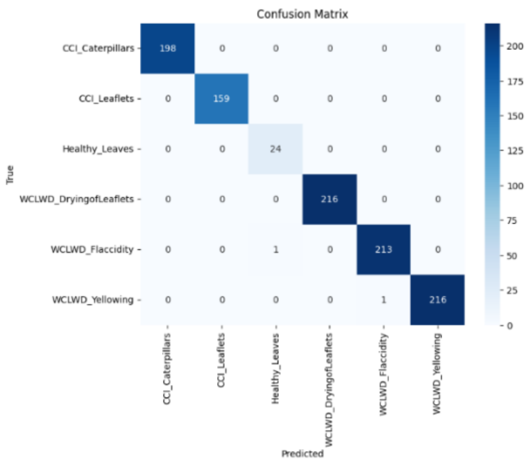

Fig. 4. Confusion matriks CNN+LSTM

The confusion matrix in Figure 4 illustrates the prediction accuracy of the model across the six tested classes. The results indicate that the majority of samples were classified correctly, as evidenced by the dominant values along the main diagonal. For instance, the CCI_Caterpillars class was accurately detected in 198 samples, CCI_Leaflets in 159 samples, Healthy_Leaves in 24 samples, and each of the WCLWD disease classes was identified with over 213 samples. Misclassifications occurred only in very small numbers, such as one Healthy_Leaves sample being mispredicted as WCLWD_Flaccidity. Overall, these results demonstrate that the CNN-BiLSTM model achieves high classification performance with minimal error rates..

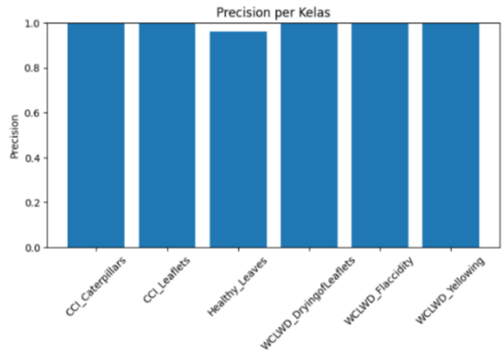

Fig. 5. Precision per-class CNN+LSTM

Figure 5 displays the precision values for each class of coconut leaf images: CCI_Caterpillars, CCI_Leaflets, Healthy_Leaves, WCLWD_DryingofLeaflets, WCLWD_Flaccidity, and WCLWD_Yellowing. Overall, nearly all classes achieved precision values close to 1, indicating that the model rarely produced false positives for their respective classes. Only the Healthy_Leaves class exhibited a slight decrease in precision, suggesting a tendency for misclassification with other classes that have visual similarities. This confirms that the model performs exceptionally well in recognizing the majority of disease symptoms and healthy conditions in coconut leaves.

TABLE II. PREDICTION RESULT EVALUATION

No	*Images*	*Model Name*	*Predicted Label*	*Confidence (%)*	*Patch Based*
0	CCI_1_32jpg.rf	CNN	CCI_Caterpilas	100	False
1	CCI_1_32jpg.rf	CNN + LSTM	CCI_Caterpilas	99.53	False
2	CCI_1_32jpg.rf	CNN + LSTM GRID	CCI_Caterpilas	91.43	True
3	CCI_1_32jpg.rf	CNN + LSTM Otimal	CCI_Caterpilas	63.18	False
4	CCI_1_32jpg.rf	CNN + BiLSTM	CCI_Caterpilas	99.97	True
5	Healthy_Leaf_90.jpg	CNN	Healthy_Leaves	99.99	False
6	Healthy_Leaf_90.jpg	CNN + LSTM	CCI_Leaflets	46.76	False
7	Healthy_Leaf_90.jpg	CNN + LSTM GRID	WCLWD_Driyingofleaflets	56.28	True
8	Healthy_Leaf_90.jpg	CNN + LSTM Otimal	Healthy_Leaves	48.87	False
9	Healthy_Leaf_90.jpg	CNN + BiLSTM	Healthy_Leaves	100	Trus
10	IMG_2837.jpg	CNN	CCI_Leaflets	99.63	False
11	IMG_2837.jpg	CNN + LSTM	CCI_Leaflets	91.83	False
12	IMG_2837.jpg	CNN + LSTM GRID	CCI_Leaflets	96.01	True
13	IMG_2837.jpg	CNN + LSTM Otimal	Healthy_Leaves	47.75	False
14	IMG_2837.jpg	CNN + BiLSTM	CCI_Leaflets	100	True
Etc.					

Table II displays a comparison of the prediction results for coconut leaf images using several model architectures: CNN, CNN+LSTM, CNN+LSTM Grid, CNN+LSTM Optimal, and CNN+BiLSTM. The addition of CNN+LSTM Grid, CNN+LSTM Optimal, and CNN+BiLSTM aimed to provide more options for the accuracy achieved. Each row shows information about the image name, predicted label, confidence level (%), patch-based approach (True/False), and the model file used.

Overall, it is evident that the CNN and CNN+BiLSTM models tend to provide higher and more stable confidence levels, often approaching 100%. For example, the image CCI_1_32 was successfully predicted as CCI_Caterpillars with 100% confidence by CNN and 99.97% confidence by CNN+BiLSTM. Meanwhile, the CNN+LSTM model and its variations (Grid and Optimal) showed fluctuations in confidence levels, and there were even cases of misclassification, such as the image Healthy_leaf_90.jpg being predicted as CCI_Leaflets (46.76%) or WCLWD_DryingofLeaflets (56.28%).

This finding confirms that the integration of BiLSTM contributes significantly to improving prediction stability and reducing misclassification errors. The patch-based approach used in some models also influenced the variation in results, as this method was able to improve predictions for images with more complex symptoms. Overall, this table demonstrates that pure CNN and CNN+BiLSTM are more reliable architectures compared to the CNN+LSTM variations for the case of coconut leaf disease identification.a.

Deployment

This stage involves the process of integrating the built model into a mobile-based application. Implementing the CNN and LSTM model into a mobile application requires effective integration between the machine learning backend and the application frontend. In this research, the trained model is run on a local server using a Flask API to provide prediction services. To allow the Flutter-based mobile application to access this API, Ngrok is used as an intermediary. Ngrok functions by creating a tunnel from the localhost to the internet, enabling the local server to be accessed via a temporary public URL. Through this mechanism, testing can be conducted directly from a mobile device without the need for permanent deployment to an external server.

The use of Ngrok provides significant advantages during the development phase, particularly in API testing and integration between system components. It allows developers to evaluate the performance of the CNN+LSTM model on the mobile application in real-time, both in terms of response speed and prediction accuracy. Furthermore, this strategy also minimizes technical obstacles during initial development, as it does not require cloud-based server infrastructure. Thus, Ngrok plays a vital role in bridging the transition from the model research phase to initial implementation in the mobile application.

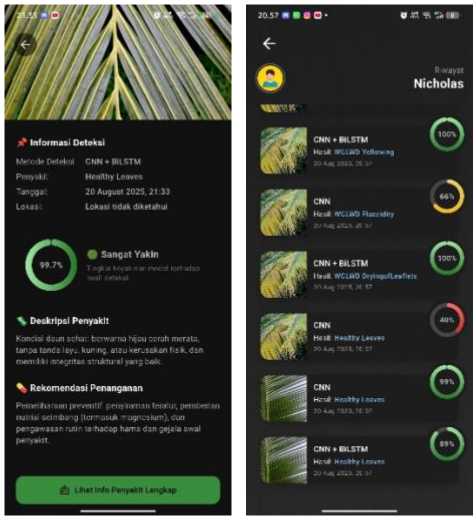

Fig. 6. Mobile application disease prediction results

Based on the implementation results of the palm leaf disease detection system using Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) displayed on the mobile application, the model successfully identifies leaf conditions with a high degree of confidence. In a sample detection, the system shows the classification result for a healthy leaf (Healthy Leaves) with an accuracy of 99.7%, accompanied by supporting information such as a description of the leaf's visual condition bright green in color without signs of wilting, yellowing, or structural damage. The application also provides preventive treatment recommendations, including regular watering, balanced nutrition, and routine monitoring for pests and diseases. These results prove that the integration of CNN and BiLSTM not only enhances detection accuracy but can also be implemented into an interactive mobile application to support farmers in real-time plant health monitoring.

IV. CONCLUSION

Based on the research results, it can be concluded that the implementation of Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) in the palm leaf disease detection system is capable of delivering excellent classification performance across six leaf condition categories, achieving an accuracy of up to 99.7%. The data preparation process which included resizing, gridding, and labeling proved effective in enhancing image readability by the model. Meanwhile, the integration of CNN for spatial feature extraction and BiLSTM for sequential data understanding resulted in more stable and accurate predictions compared to pure CNN or CNN+LSTM models.

Evaluation results from the confusion matrix, accuracy graph, and precision per class demonstrated a dominance of correct predictions with minimal error rates, particularly in the CNN and CNN+BiLSTM models, which consistently produced confidence levels close to 100%. Furthermore, the integration of the model into a Flutter-based mobile application via Flask API and Ngrok successfully facilitated real-time detection, proving that the system is not only academically robust but also holds practical potential in supporting palm oil farmers to monitor crop health quickly, efficiently, and with precision.

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