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AnAI: A Mobile Application to Predict Household Termite Infestation Using Machine Learning from Smartphone Sensor Data

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Abstract

Termite attacks result in substantial economic and environmental losses annually. Current prediction methods are both labor-intensive and costly. To address this issue, the study presents "anAI," a mobile application that employs deep learning and machine learning models to forecast termite infestations, identify wood types, and assess the likelihood of attacks using environmental data. The research utilized three deep learning models—MobileNetV2, AlexNet, and Convolutional Neural Network (CNN)—for image classification, with CNN achieving the highest accuracy rates. Additionally, machine learning models such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM) were employed to predict termite attack likelihood, with SVM proving superior. Logistic regression classified likelihood into three levels: certain, likely, and unlikely. The study collected 181 wood samples, augmenting them to 506 images, and achieved satisfactory accuracies for termite infestation and wood type identification. "anAI" delivers real-time predictions, facilitating proactive termite management by utilizing environmental parameters like temperature, humidity, and wood moisture. This research underscores the importance of integrating advanced intelligent systems into pest management, enabling early detection and mitigation of termite infestations, thereby minimizing property damage, and supporting sustainable practices.

Keywords
Termite infestation, Termite attack likelihood, Deep learning, Machine learning, Logistic regression

1. Introduction

Termites *(Isoptera)* play a huge role in the ecosystem as they help break down and decompose dying trees and plants which in turn improve soil pH, organic carbon content, water content, and porosity of the land (Ghaly & Edwards, 2011). However, when termites start to consume the wood in households, buildings, and residential homes, they are a harmful pest (Ahmad, et al., 2019). According to the US Environmental Protection Agency (EPA), an estimated $5 billion in property damage is caused by termites. Their ability to infest and weaken the structural integrity of a structure makes them a complex problem for homeowners and businesses.

Termites also cause $40 billion in damages to agricultural crops, resources, and lumbers (Ahmad, et al., 2019). These pests are abundant and commonly found in tropical and subtropical regions in the world like the Philippines. Subterranean termites like *Coptotermes vastator Light, Nasutitermes luzonicus Oshima, Mactroterme gilvus Hagen, Microerotermes losbanoseenis Oshima* cause millions of dollars of economic loss both to urban and rural residents (Acda, 2013). The economic impact is significant, with the repair and renovation cost skyrocketing and environmental concerns arising from the use of chemical pesticides to combat infestations. Despite efforts to treat wood with chemicals, research, such as Kartal et al. (2007), reveals that termites can still penetrate treated wood, although the percent mass loss is lower than non-treated wood.

Grace (2013) further emphasizes variability in the effectiveness of chemical treatment across different wood species. While some show resistance, the sapwood of certain species remains entirely susceptible to termite infestation. These findings collectively indicate that chemical treatment enhances wood resistance but does not ensure complete immunity, underscoring the necessity for a comprehensive and sustainable approach to termite infestation management. Termite infestations are a serious concern for homeowners, property managers, and the economy since they are pervasive and frequently difficult to identify and treat.

Early detection of termite attacks and infestations is crucial as it allows homeowners to minimize property damage, lower treatment costs, preserve property value, prevent the spread of infestations, and support sustainable pest control practices (Oi, 2022). Moreover, termite attacks can be attributed to different environmental factors such as wood moisture, type of wood cellulose-containing materials, soil mulch, cracks and openings, humidity, and temperature (Oberst, et al., 2019; Santos, et al., 2010). Traditional methods of identifying the attack include conducting surveys with people regarding the conditions of termite attacks in their houses; and homeowner interviews to collect data on the building's history, frequency, and intensity of termite attacks (Novita, et al., 2020). Another method is through visual inspection by experts, which can be costly and time-consuming. These methods can also miss early signs of infestations, resulting in delayed intervention.

As these termites continually pose a threat to the safety of the people through the destruction of their houses and buildings, and despite the existence of available chemicals for termite resistance, which termites can still penetrate, there is an urgent need for innovative and efficient approaches to identify what wood types and environmental conditions encourage termites to attack. Leveraging modern technologies like deep learning and machine learning can revolutionize the ability to predict and manage these attacks.

1.1. Objectives

The study aims to develop a multimodal approach that combines deep learning model and machine learning in predicting the likelihood of termite attacks. Through deep learning, particularly, Convolutional Neural Network (CNN), one can extract feature of images of non-infested wood and infested wood and make accurate predictions; and with machine learning, one can learn to discern subtle indicators and patterns of environmental condition in relation to an impending termite infestation. This approach enables a real-time, proactive, and accurate prediction system, empowering homeowners and pest control professionals to address potential termite threats before damage occurs.

The adaptability of deep learning and machine learning in recognizing visual cues and patterns positions them as a powerful tool in safeguarding households against the destructive nature of termite infestations. Furthermore, employing Kohaa as an external camera application capable of capturing both images and real-time data regarding temperature and humidity, alongside a wood hygrometer for assessing wood moisture, has been integral in monitoring termite infestations within household settings. Moreover, this research considers the specific wood varieties commonly targeted by termite attacks. Hence, this study was conducted.

2. Methods

2.1. Proposed machine and deep learning algorithms

Table 1 shows the different outputs that AI models predicted. Each output is divided into three groups. Specifically, Output 1 is the prediction of the deep learning (DL) models—CNN, AlexNet, and MobileNetV2—classifying the infested wood and non-infested using feature learning from the different images. The second prediction of the DL models is the multi-classification of the different types of wood, namely: Mahogany, Molave, Gmelina, and Plywood. Like output 1, the DL model utilized the different features and characteristics of the wood in predicting. Lastly, the machine learning (ML) model, SVM and AN, would predict the likelihood of termite attacks based on the interaction of the different environmental conditions classified into three categories: Certain, Likely, and Unlikely.

Table 1. Different outputs for the AI models

Output Number	Description	AI Models Used for Prediction
1	Infested and Non-Infested Wood	CNN AlexNet MobileNetV2
2	Type of Wood (Mahogany, Molave, Gmelina, and Plywood)	CNN AlexNet MobileNetV2
3	Likelihood of Termite attack (Certain, Likely, Unlikely)	SVM ANN

2.2. Data augmentation

The image-based dataset was augmented from 181 images to 506 images through flipping, rotating, and scaling to enhance the diversity of the dataset. Furthermore, adhering to a 70-30% ratio following Buddhavarapu and Jothi J (2020) and Purohit et al. (2022), this study allocated 354 images for training and 152 images for testing the deep learning model. This distribution ensured robust training while allowing for comprehensive evaluation during testing.

2.3. Deep learning implementation

This study utilized three deep-learning models to predict the infested and non-infested wood, and the different wood types. These DL models include CNN, AlexNet, and MobileNetV2. Given that these models lacked pre-existing classes related to termite detection, we initiated training from scratch, ensuring that the networks did not benefit artificially from the accuracy associated with the utilization of pre-trained weights.

In this study, supervised learning mode was utilized with input, representation, and metrics to compute tensors in the hidden layer. CNN employed numerous identical neurons across its layer to calculate computations for large models with a minimal number of parameters. Each layer followed a sequence of regression that was denoted by an activation function; this process was called forward propagation as shown in the equations below:

$$Input = z = \sum_{i=1}^{n} (w_i * x_i) + b \tag{1}$$

$$Output = \alpha = \sigma\,(\mathrm{z}) \tag{2}$$

where:

$w_i = weights$
$b = bias$
$z = weighted\ sum$
$\sigma =$ activation function
$\alpha = output$

2.3.1. Output 1: Binary classification of infested and non-infested wood samples

The Binary Classification between the Infested and Non-Infested Wood samples using the Deep Learning Models: CNN, AlexNet, and MobileNetv2. The three models were able to classify the distinction of each classification using the distinct features for each class: Infested and non-infested wood. The infested class showed a distinct pattern like the tunnels and mud that were damaged by termites. On the other hand, the non-infested class showed no signs of an attack pattern of termite attacks. These distinct features for each class were crucial for both phases, which are the training and testing phases, of classifying both classes: infested and non-infested wood.

2.3.2. Output 2: Multi-classification of the types of wood

The multi-classification prediction using CNN, AlexNet, and MobileNetV2 for the various wood types including Mahogany, Gmelina, Molave, and Plywood was employed. In order to determine and classify the various features of each wood type, these deep-learning architectures have been used. Through training and testing on 5-fold cross validation on labeled wood-type datasets, the models have learnt to distinguish the differences of the variation of the textures and the characteristics of each wood classification.

During the training process, the models have been trained to distinguish Molave's dark brown hue and grain patterns unlike Gmelina's smooth texture. While Gmelina with its light color and uniform texture, has become a distinct category. Additionally, the color reddish-brown has been identified as Mahogany, setting it apart by its uniqueness and from other wood varieties. In contrast, a Plywood has a smooth layered structure and the lack of grain appearance, which presents another classification challenge. The CNN model effectively determines the extraction and analysis of these special visual characteristics for each type of wood using iterative training cycles to facilitate classification of wood samples according to their category. In addition, they have been able to recognize these wood types when painted by teaching models to focus on the underlying textures and structural characteristics rather than surface appearance alone.

The wood-type data were augmented from 181 to 506 images by iterative adjustments based on data augmentation. Data augmentation has enabled the models to be exposed to a wider range of images, allowing them to learn robust characteristics indicative of every wood type, regardless of surface variations induced by paint. In doing so, it empowered the models to classify unseen data more accurately and improve their overall efficiency in wood classification tasks.

2.4. Model evaluation

All models are evaluated using both loss functions and performance metrics. Loss function plays a significant role in both deep learning and machine learning since it measures the disparity of the expected and actual values (Wang, et al., 2022). Moreover, the metrics mean squared percentage error (MSPE) or root mean squared error (RMSE) are the ones usually employed and relied on by the researchers when evaluating the effectiveness of regression models. The equations for evaluating the models' loss functions are shown below:

$$RMSE = \sqrt{\sum \frac{\left(y_{pred} - y_{ref}\right)^2}{N}} \tag{3}$$

$$MSE = \frac{\sum (y_i - \hat{y}_i)^2}{n} \tag{4}$$

RMSE is necessary as it provides a comprehensive measure of the accuracy of the predictive model. By averaging the squared errors across all of the dataset's data points, mean square error (MSE) measures a prediction model's overall accuracy.

On the other hand, evaluating the performance of the model was essential to every deep learning pipeline, and the confusion matrix was one of the metrics to measure the precision and recall given the predicted and real labels of the model (Rahaman, et al., 2023). Presented below are the equations of accuracy, precision, and F1-score.

$$Accuracy = \frac{TN + TP}{TP + FP + FN + TP} \tag{5}$$

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$F1\ Score = 2\ x\ (\frac{Precision\ x\ Recall}{Precision + Recall})\ x\ 100 \tag{7}$$

3. Data Collection

This study used the Kooha application for capturing the image and measuring the humidity and temperature of the household. Consequently, a wood hygrometer was integrated into the study to measure the wood moisture.

During the image acquisition, a mobile, Vivo V21e with 2.3 Ghz Snapdragon 720G Octo-core with 12 Android Version and a 64 MP, 26 mm wide camera was used. In addition, images were captured under field conditions with natural lighting using a vertical standard orientation taken from a constant distance of 25 cm from the point of the subject (Wang, 2022), with a 90° angle (Tetila, et al., 2020). Moreover, the mobile phone was mounted to a camera holder to photograph the images. In some cases where there was an absence of light, the flash of the mobile phone was utilized. In line with this, the supporting mount ensured a steady and stable positioning of the mobile phone during image capture, minimizing potential blurring or distortion in the photographs. In addition, the mobile phone holder was adjustable depending on the necessary position during the photograph. These guidelines ensured that the images provided a clear and informative representation of the termite infestation on the wood, facilitating accurate analysis and assessment. Figure 1 shows the setup of the image acquisition.

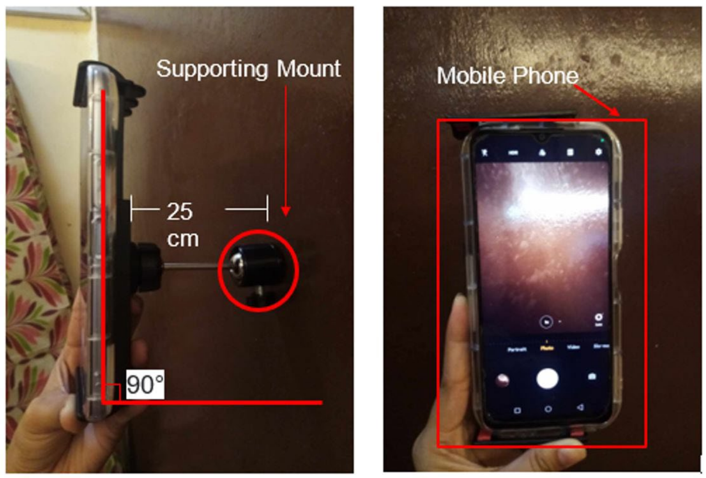


Figure 1. Diagram of the 90° - 25cm rule in capturing an image

4. Results and Discussion

After the training and testing phases, the deep learning models and machine learning models were evaluated based on its loss functions and performance metrics. Moreover, the AI model selection for creating the Mobile Application is also based on the overall performance of the models.

4.1. Loss functions of the DL models in predicting the termite infestation in the wood

Table 2 compares the performance of three deep learning models: MobilenetV2, AlexNet, and CNN. Mobilenetv2 achieves an RMSE of 0.53 and MSE of 0.28, while AlexNet records an RMSE of 0.42 and MSE of 0.17. In comparison, CNN demonstrates superior performance with an RMSE of 0.27 and MSE of 0.07. In Comparing the performance of three deep learning models – Mobilenetv2, AlexNet, and CNN – across the metrics of RMSE and MSE, it's evident that the CNN model consistently outperforms the others.

Table 2. Comparison of the loss functions of the DL models in predicting termite infestation

Deep learning models	Loss functions	
	Root Mean Squared Error (RMSE)	Mean Squared Error (MSE)
MobilenetV2	0.53	0.28
AlexNet	0.42	0.17
CNN	0.27	0.07

Lower error rates were observed with the CNN model in both RMSE and MSE metrics. In line with this, lower RMSE and MSE values indicate accurate predictions, as smaller squared difference implies a closer alignment between the predicted and the actual values. This indicates that CNN is more adept in predicting accurately the infested wood from the non-infested wood samples compared to Mobilenetv2 and AlexNet. The superior performance of CNN means that its basic architecture and training process are better suited for the task, due to its ability to capture more intricate patterns and features in the wood images.

4.2. Loss functions of the DL models in predicting the types of wood

Table 3 shows the comparison of the loss functions among the three deep learning models in predicting the type of wood. The RMSE and MSE values of the deep learning models had a relatively poor performance in predicting the type of wood. Across all three models (Mobilenetv2, AlexNet, and CNN), the RMSE values range from 1.08 to 1.49, indicating substantial deviations between the predicted and actual types of wood. Similarly, the MSE values range from 1.17 to 1.42, further indicating a notable degree of error in the predictions. These relatively high RMSE and MSE values means that the models struggled to accurately classify the type of wood, indicating challenges in capturing the nuanced features or patterns associated with different wood types.

Table 3. Comparison of loss functions of the DL models in predicting the types of wood

Deep learning models	Loss functions	
	Root Mean Squared Error (RMSE)	Mean Squared Error (MSE)
MobilenetV2	1.08	1.17
AlexNet	1.19	1.42
CNN	1.05	2.24

4.3. Loss functions of the ML models in predicting the likelihood of termite attacks

Table 4 presents the comparison of loss functions between the ANN and SVM models in predicting the likelihood of termite infestations. The SVM model exhibits superior accuracy, evident from its significantly lower RMSE of 0.45 while having a MSE of 0.21, compared to the ANN model. The SVM model showed higher results for both RMSE and MSE indicating that it created less accurate predictions and encountered more deviations from the actual outcome.

Table 4. Comparison of loss functions of the ML models in predicting the likelihood of termite attack

Deep learning models	Loss functions	
	Root Mean Squared Error (RMSE)	Mean Squared Error (MSE)
ANN	0.45	0.21
SVM	0.33	0.10

These differences reinforce the fact that SVM is more effective compared to the ANN model in capturing underlying patterns in the data. As a result, SVM's superior generalization capability allows it to perform well on unseen data. The use of SVM ensures that the model is not only accurate in its predictions but also robust against overfitting, which is a crucial advantage when dealing with various environmental conditions affecting termite infestation likelihood. This proficiency allows SVM to become an optimal choice for the integration of the system that requires both high reliability and accuracy.

4.4. Performance of the DL models in predicting termite infestations and types of wood

In order to detect the termite infestation of the wood for Output 1 and classifying the wood types for Output 2, Table 5 displays the AI models performance comparison. The CNN demonstrated a superior performance to all other models for Output 1 based on their evaluated performance metrics such as Classification Accuracy, Precision, and F-1 score after the 5-times cross-validation. With the architecture used in the CNN, it was able to gain the highest Accuracy score of 81.22% compared to 59.88% and 49.71% of MobileNetV2 and AlexNet. Additionally, it surpasses MobileNetV2 and AlexNet by 74.73% in terms of Precision score of 47% and 46% respectively. Consequently, CNN also attained a high F-1 score of 80% compared to the other models. The performance of CNN was also consistent in the prediction for Output 2 with an accuracy of 75.23%, precision of 75.31%, and an F-score of 75%.

Table 5. Performance comparison of the DL models in predicting termite infestation and the types of wood

Output	DL model used	Accuracy	Precision	F-1 score
Infested or Non-Infested Wood	MobilenetV2	58.55%	47%	28%
	AlexNet	49.71%	46%	46%
	CNN	81.22%	74.73%	80%
Type of Wood (Mahogany, Molave, Gmelina, or Plywood	MobilenetV2	43.09%	43%	43%
	AlexNet	38.67%	38%	38%
	CNN	52.23%	75.31%	75%

In addition, the other AI models: AlexNet and MobileNetV2 had low accuracy, precision, and F-1 scores which are below the 70% threshold as mentioned by Adoptante (2024). Factors such as overfitting during the training phase due to the limited and unbalanced training data impacted the overall performance of the AlexNet and MobileNetV2 in the binary classification of wood infestation and multi-classification of the wood types. Furthermore, misclassification occurred in identifying infestation and the types of wood often occurred when images from different category (i.e., infested or not, and types of wood) look relatively similar, thus, image features are also similar. The models have difficulties because of the likeness of a slightly infested wood and infested wood, which resulted in low levels of accuracy, precision, and F1-score.

Compared to MobileNetV2 and AlexNet, which have more complex architectures with additional layers and parameters, CNN's architecture is basic and simple. This simplicity mitigated the risk of overfitting, where irrelevant patterns such as dust and molds present in the training data led to optimization and classification difficulties and performance issues. With fewer layers and parameters, CNN had a reduced capacity to memorize training data, resulting in better generalization and performance compared to MobileNetV2 and AlexNet. Moreover, CNN's architecture required fewer computational resources for training, making it more efficient and practical.

4.5. Performance of the ML models in predicting the likelihood of termite attacks

Table 6 presents the performance comparison of the two machine learning algorithms in predicting the likelihood of termite attacks within households. The analysis of the results shows that SVM demonstrated superior performance in all three metrics listed (Accuracy, Precision, and F1-Score) after 5-fold cross-validation, outperforming ANN. Doing the 5-fold cross-validation, increased the confidence in the models' performance, reducing the chance that the results are due to random fluctuations in the data and decreasing the likelihood of overfitting.

Table 6. Performance comparison of the ML models in predicting the likelihood of termite attacks

ML models used	Accuracy	Precision	F-score
SVM	89.19%	93.75%	88%
ANN	86.49%	88.2%	85.71%

With a higher classification accuracy of 89.19% compared to the ANN model's 86.49%, the SVM model correctly classifies data points and achieves more accurate overall predictions. This indicates that SVM is better at predicting the likelihood of termite attacks. Additionally, it exhibits a higher precision of 93.75% compared to ANN’s 88.2%, meaning that SVM is better at identifying only the relevant data points and filtering out irrelevant ones. Furthermore, with an F-score of 88% compared to 85.71%, it indicates that the SVM model has better overall effectiveness in predicting the likelihood of termite attacks compared to ANN.

5. Proposed multimodal prototype mobile application: anAI

5.1. General workflow of the prototype

The name of the Multimodal Prototype Mobile Application is coined "anAI", which is inspired by the Cebuano word “anay,” which means termites, integrating it with "AI" for Artificial Intelligence, symbolizing a blend of local language and modern technology.

The AI framework of the Multimodal Prototype Application is TermIEte. It comprises the cascaded model of CNN and SVM that can predict the presence of termite infestation in the wood, the type of wood, and the likelihood of termite infestations for the non-infested samples. The selection of the CNN and SVM as the framework of the Multimodal Prototype Application was anchored by its overall performance during the training and testing phase by having the loss function and performance metrics by predicting the different outputs. Moreover, Figure 2 shows the basic workflow of the TermIEte. The process begins with the input of an image-based dataset containing samples of both infested and non- infested wood.

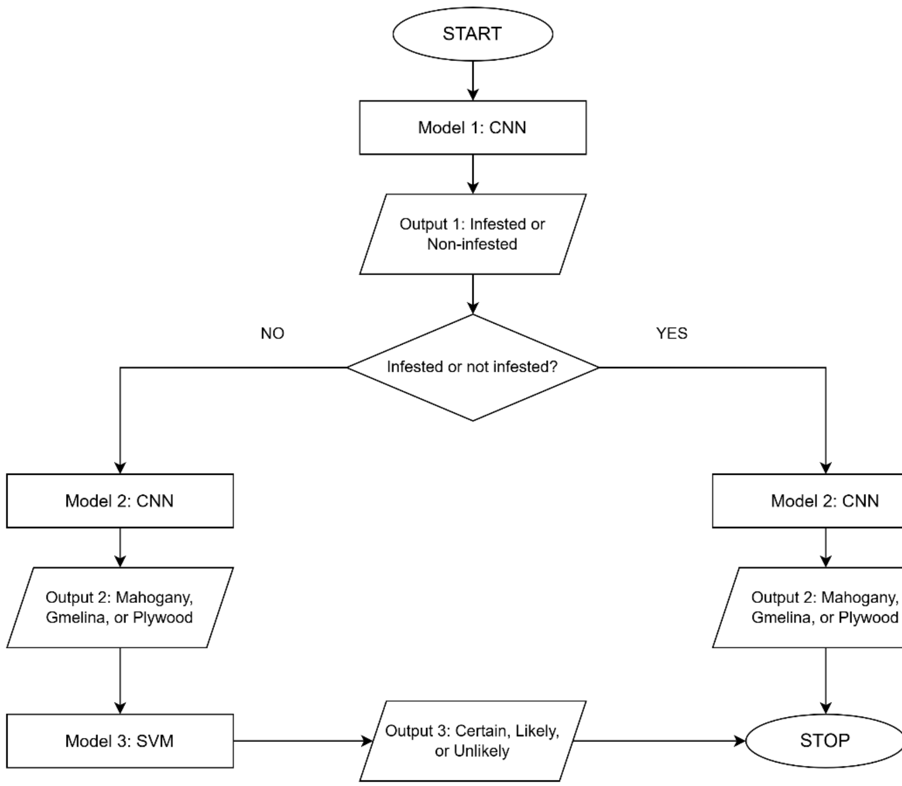


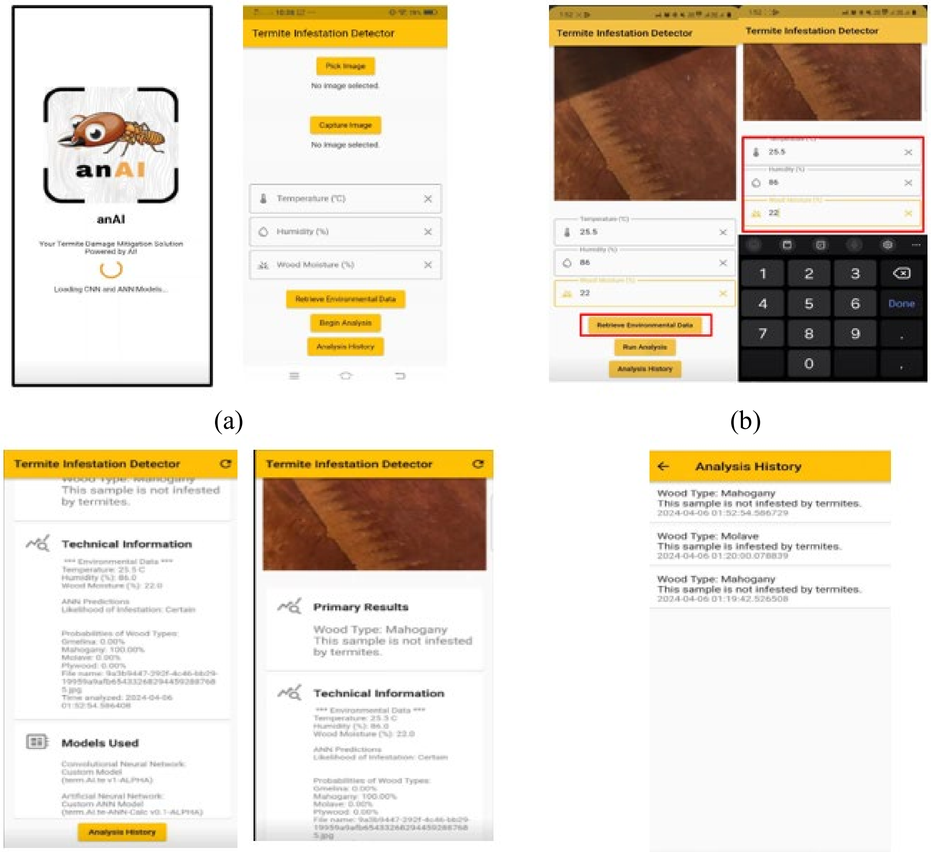
Figure 2. Basic workflow of TermIEte

Utilizing its trained weights and ReLU activation function, the first CNN model classifies each image, determining whether it depicts an infested or non-infested wood sample. Following every convolution, a maximum pooling layer is used. Subsequently, a second CNN model, employing the same architecture with the sigmoid function, predicts the specific type of wood—Mahogany, Molave, Gmelina, or Plywood. If the image is classified as non-infested, the process proceeds to the next model, SVM, which evaluates the likelihood of termite infestation based on user-input environmental conditions. The SVM model then classifies the likelihood as Certain, Likely, or Unlikely.

5.2. Mobile application interface

The application interface provides users with access to anAI's various features, designed to be user-friendly and intuitive. It includes the dashboard, Environmental Conditions input, prediction results of the anAI, and the Analysis History as shown on the Figure 3. When users initially open the app, they are welcomed by the loading screen displaying the app's logo, name, and slogan, along with the loading progress of the CNN and ANN Models Figure 3a.

After capturing the image of the wood, users are given the choice to access environmental condition readings via the backend Weather API by selecting "Retrieve Environmental Data" as shown in Figure 3b. Furthermore, the mobile application interface presents the predictions of various outputs. These outputs are divided into two sections: Primary Results and Technical Information as shown in Figure 3c. Moreover, this Analysis History feature allows users with the ability to track their analysis history, facilitating informed decision-making and enabling comparisons between different analyses over time as shown in Figure 3d.



(a) (b) (c) (d)

Figure 3. Mobile application overall interface: (a) dashboard, (b) environmental conditions input, (c) prediction results of the anAI and (d) analysis history

5.3. Functionality overview of the proposed prototype

As shown in Figure 4, the process begins with the input of an image-based dataset containing samples of both infested and non-infested wood. Utilizing its trained weights and ReLU activation function, the first CNN model classifies each image, determining whether it depicts an infested or non-infested wood sample. Following every convolution, a maximum pooling layer is used. Subsequently, a second CNN model, employing the same architecture with the sigmoid function, predicts the specific type of wood—Mahogany, Molave, Gmelina, or Plywood. If the image is classified as non-infested, the process proceeds to the next model, SVM, which evaluates the likelihood of termite infestation based on user-input environmental conditions. The SVM model then classifies the likelihood as Certain, Likely, or Unlikely.

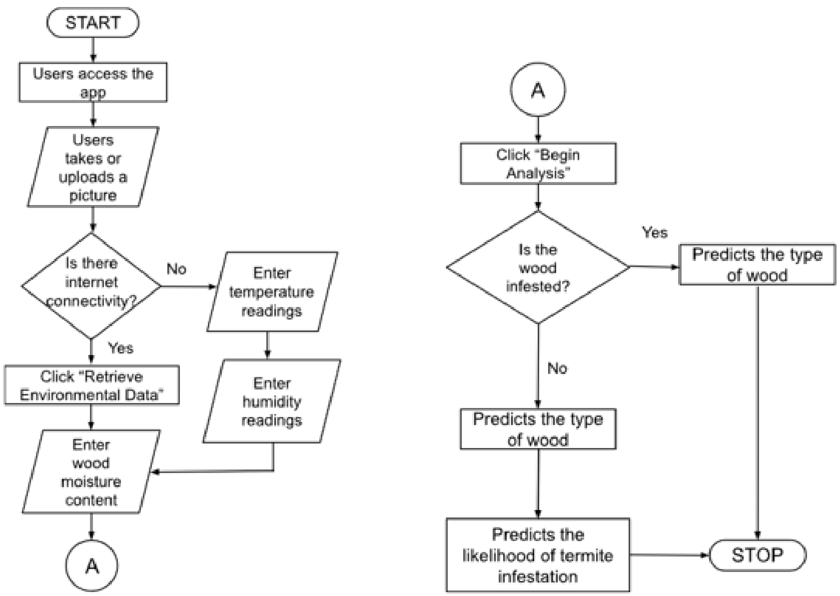


Figure 4. anAI mobile application process flow chart

5.4. Testing and validation of the proposed prototype

The testing and validation of the mobile application involved conducting 100 tests to compare the results of the anAI prototype mobile application with manual identification by wood and termite experts. Moreover, the Manual testing was conducted for all three outputs of the mobile application. The first output, which is the classification of the termite infestations, was carried out by observing existing conditions and checking for any signs of termite infestation on the wood such as the presence of mud tunnels and tubes. The second output, which is the prediction of the type of wood by examining the wood characteristics such as wood pattern, grain (especially the end and edge grain), texture, color, weight, hardness, and the presence of burl knots, with the assistance of a wood expert. Lastly, the manual prediction associated with the third output considers the threshold of environmental conditions to identify the likelihood of termite infestation with the termite experts.

Table 7. Validation of the proposed prototype in predicting the different outputs

No. of trials	Prediction of the infested and non-infested wood			Prediction of the wood types			Prediction of the likelihood of termite attacks		
	Manual	AnAI	% Accuracy	Manual	AnAI	% Accuracy	Manual	AnAI	% Accuracy
100	100	86	81%	100	78	78%	100	89	89%

According to the results in Table 7, the application demonstrated robust performance, achieving an accuracy of 86% in correctly distinguishing infested from non-infested wood. Additionally, it exhibited a 78% accuracy in accurately predicting wood types and an 89% accuracy in forecasting the likelihood of termite attacks. Factors that led to misclassifications of the different predictions include the lighting conditions during the capturing of the image, the quality of the camera, the distance and angle while capturing the image, and variations in paint color applied to the wood. Table 6 shows the results of the validation.

6. Conclusion

The result of the study led the researchers to successfully developed a Multimodal Prototype Mobile Application using the frameworks Al model CNN and SVM in predicting the three outputs: classification of termite infestation in wood samples, multi classification of wood types, and the prediction of the likelihood of termite attacks in the household setting. The three outputs using CNN and SVM evaluation results demonstrated a condescending performance compared to other models, namely: MobilenetV2, AlexNet, and ANN. The CNN and SVM evaluation results demonstrated superior performance compared to other AI models such as MobilenetV2, AlexNet, and ANN. Furthermore, the prediction capability of the Multimodal Prototype Mobile Application in the likelihood of termite attacks in households closely aligns to the Optimal Foraging Theory. This theory suggests that the foraging of termite and its attacking behavior is influenced by wood availability, nest location, and environmental conditions such as temperature, moisture, and humidity (Cornelius, 2010). The Multimodal Prototype Mobile Application is remarkably the first for detecting termite infestation in the Philippines with the application of deep learning and machine learning techniques. It also demonstrated a practical application of deep learning and machine learning algorithms in predicting the likelihood of termite attacks within the household setting, facilitated by working on an intuitive and simple interface that can be run on an Android Mobile phone.

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