Deep Learning-Based Earthworm Health Monitoring and Vermicompost Quality Recognition for Smart Organic Farming

Ms. Shital Avinash Jedhe[1], Dr. Ganesh Gorakhnath Taware[2]
[1,2]Department of Computer Engineering, Dattakala Group of Institutions, Faculty of Engineering, Swami-Chincholi Bhigwan, India

Abstract—**The vermicomposting process is environmentally friendly and sustainable as it involves transforming organic waste into fertilizer rich in nutrients through the biological processes of earthworms. The health status of the earthworms and the quality of the vermicompost are two very essential parameters that affect the effectiveness and sustainability of the vermicomposting process. The traditional methods used to evaluate vermicompost quality and earthworm health involve laboratory testing and visual inspection, which are time-consuming, subjective, and often unsuitable for large volumes of vermicompost. This paper proposes an automatic system for vermicompost quality assessment and earthworm health monitoring using deep learning algorithms. To boost dataset diversity and improve generalization, additional techniques, such as rotation, flipping, zooming, and brightness adjustment, were used alongside image cropping and scaling for augmentation. Three deep learning approaches, such as CNN, CNN-SVM, and ABCNN, were applied and evaluated in the research. Indicators such as accuracy, precision, recall, and F1-score were among the most common performance metrics. Based on the experimental results, the proposed attention-based approach was more effective at learning discriminative visual features of earthworm morphology and vermicompost properties than other approaches. The proposed architecture will facilitate sustainable organic farming by enabling intelligent monitoring of vermicomposting.**

Index Terms—**Vermicomposting, Earthworm Health Monitoring, Vermicompost Quality Assessment, Deep Learning, Transfer Learning, Convolutional Neural Network (CNN), CNN-SVM, Attention-Based CNN, Image Classification, Smart Agriculture, and Computer Vision.**

I. INTRODUCTION

The growing need for ecologically friendly farming methods and efficient organic waste management has drawn significant attention to sustainable agriculture in recent years. Vermicomposting is one of the most sustainable biological processes, converting organic waste into nutrient-rich organic fertilizer through the activity of earthworms. The resulting vermicompost increases water retention capacity, boosts microbial activity, improves soil fertility, and encourages healthy plant growth. As a result, vermicomposting is now a crucial part of contemporary organic farming systems.
It is important to understand that earthworms are key participants in vermicomposting, as they accelerate the decomposition of organic materials and improve their effectiveness. If an earthworm is healthy, it will have a normal structure, be very active, be the same color throughout, and feed well, thus producing good compost. On the other hand, environmental stressors that can harm earthworms include high moisture levels, temperature changes, substrate degradation, pathogens, and toxins. Sick earthworms will exhibit signs such as color changes, shrinkage, damaged bodies, reduced activity, and abnormal shapes.
Apart from the health of the earthworms, the quality of the vermicompost is also an important criterion for assessing the efficiency of the vermicomposting process. Good-quality vermicompost is distinguished by dark coloration, granular consistency, homogeneity, adequate moisture content, and effective breakdown of organic matter. Poor-quality vermicompost, on the other hand, will be characterized by undecomposed organic matter, a high moisture content, an uneven structure, and inadequate nutrient content.

Conventionally, methods for assessing earthworm health and evaluating vermicompost have involved manual inspection and lab analysis. Although they are quite reliable, these methods tend to be costly, cumbersome, and depend greatly on experts. Additionally, large-scale vermicomposting facilities will need to conduct such tests regularly; thus, manual assessment becomes difficult and prone to human errors.

Advancements in recent years in deep learning, computer vision, and artificial intelligence have enabled new capabilities in automated agricultural monitoring systems. Notably, CNNs are effective across many agricultural applications, including soil analysis, object detection, plant disease identification, and image classification. Deep learning algorithms don't require manual feature extraction because hierarchical visual features can be automatically extracted from images. In addition, even with small data sets, high-precision image classification algorithms can be designed using transfer learning techniques.

Recently, advances in attention mechanisms have enabled improvements to classic CNN algorithms. In this way, neural networks can exclude irrelevant background information and concentrate on the most important parts of an image. On the other hand, when considering earthworm monitoring tasks or vermicompost evaluation, it is expected that an attention-based network can detect discriminative visual features of earthworms or vermicompost.

In light of the above-mentioned advancements, this paper proposes an approach for concurrent assessment of vermicompost quality and earthworm health status using image processing within a deep learning framework. Pictures of both healthy and unhealthy earthworms, along with good- and bad-quality vermicompost’s, are captured in a vermicompost plant under natural environmental conditions. Data preprocessing and augmentation are applied to the collected data to improve the data set's quality and the model’s generalizability. Three different classification techniques, namely, CNN, CNN with SVM, and Attention-Based CNN (ABCNN), are utilized in the research. Common performance evaluation metrics include accuracy, precision, recall, and F1-score. The proposed framework aims to develop an automated, intelligent, and reliable monitoring system that promotes effective vermicomposting practices.

II. LITERATURE SURVEY

Meghwanshi et al. [1] have conducted a review of AI-based techniques for detecting earthworms' physiological state and vermicompost quality. This study was a systematic review of the use of machine learning and deep learning algorithms to detect earthworm health signs from images. The findings revealed that computer vision-based approaches can assess earthworm health by analyzing body structure, texture, and movement features. However, this paper also revealed a critical knowledge gap: the lack of high-resolution data sets incorporating both biological and physicochemical soil characteristics.

The proposed system by Andleeb et al. [2] used computational intelligence to classify earthworms based on morphological image features. Different earthworm species were identified using both deep learning-based classification and traditional feature-based methods, such as scale-invariant feature transform (SIFT) and histogram of oriented gradients (HOG). A high level of accuracy in identifying the Eisenia fetida species was achieved during an experimental evaluation. Yet the authors have failed to consider the physiological condition of organisms within the same species.

Çelik and Uguz [3] proposed a deep learning-based system for the real-time detection of earthworm cocoons in vermicomposting environments. The proposed methodology used transfer learning of the Faster R-CNN and ResNet50-FPN architectures to recognize cocoons in intricate compost substrates. The system had an average precision (AP) of 0.89, which facilitated effective automated sorting and tracking. However, the study focused more on reproductive structures and did not determine the health of active adult earthworms.

A classification system for earthworm species based on a large number of image texture parameters was developed by Kavitha et al. [4] using a neural network. The methodology used texture features derived from multiple color channels (more than 2,000 features) to train ensemble classifiers and narrow neural networks. The experimental analysis classified approximately 100% of the genera, such as Lumbricus. Although it was very precise, it relied on static images of the worms, thereby ignoring the dynamic movements typically associated with their health.

Wang et al. [5] examined immune dysfunction in earthworms exposed to soil contaminants and chemical stressors. Physiological responses were analyzed using a combined biological stress assay and image-based pattern recognition approach. The findings showed that unique biological signatures could be used to classify different levels of health stress. Nevertheless, this was restricted to laboratory conditions, and the unification of such immune-response signatures into generalized automated transfer learning models has not been studied.

Ramazanoglu [6] studied soil health monitoring using thermal imaging and machine learning to track earthworms. The suggested methodology quantified the level of temperature change in the surroundings of an infrared sensor-monitored vermicompost and correlated it with earthworm behavioral responses. The findings showed that thermal patterns are useful for differentiating optimal and stressed habitat conditions. However, the study lacked a transfer-learning architecture for predicting thermal patterns from visual signals of earthworm health.

Kumar et al. [7] suggested a machine learning-based platform for analyzing the health of soil and its interconnection with biological indicators. Random Forest and XGBoost are ensemble learning algorithms that were used to assess the relationship between soil fertility parameters and earthworm density. The findings revealed that earthworm population density is an effective predictor of nutrient availability and soil quality. Nevertheless, the framework lacks systems for diagnosing the health status of individual earthworms (healthy or unhealthy).

Ayintareba et al. [8] have reviewed the transfer learning methods used in the biological image classification tasks. They compared pre-trained convolutional neural network models, including AlexNet and VGGNet, for health-related image recognition. The findings showed that fine-tuning pre-trained models is much better at classification with small or specialized biological predictions. Nevertheless, the study failed to investigate fine-tuning approaches specifically designed to account for morphological and textural variations in healthy and unhealthy earthworms.

Djerdj et al. [9] have suggested a deep learning-based method for observing an earthworm's response to chemical stress. They employed CNNs to analyze movement and behavioral patterns as predictors of physiological well-being. The findings showed good precision in categorizing the behavioral states of healthy or stressed individuals. However, the system is very intensive in terms of computational power because it must handle continuous video streams, which can be a major constraint for its use in long-term environmental monitoring.

Ibrahim et al. [10] suggested an Internet of Things (IoT)-based environment supervision and control framework fitted to earthworm farming settings. The system used a combination of environmental sensors and machine learning to ensure the habitat conditions were optimal for the earthworm to grow. The experiments demonstrated better environmental stability than the conventional methods of monitoring by human agents. Nevertheless, the system lacks computer vision feedback for real-time assessment of earthworm health.

Li et al. [11] proposed CenWholeNet, which is an anchor-free deep learning model that is used to identify irregular and elongated biological structures. The methodology used was center-point detection, which improved the detection of complex shapes compared to traditional object detection methods. The experiments demonstrated better performance than YOLOv5 when using non-standard object shapes. However, the model has not been tested to identify abnormalities in earthworm health, including lesions, shrinkage, or discoloration.

Tsai et al. [12] proposed a hybrid system that integrates time-series feature extraction with transfer learning for biological health monitoring. The methodology involves analyzing time-series biological data to detect dynamic variations in physiological states. The results showed an approximate 15% increase in prediction accuracy compared to models that used only static image data. However, the use of this temporal model for physiological motion and contraction patterns in earthworms has not been studied.

Nguyen et al. [13] have developed a deep learning classification model based on the EfficientNet-V3 architecture to identify different species of invertebrates. Transfer learning has been used to improve classification accuracy across several biological datasets. The model achieved approximately 95% accuracy in general invertebrate classification. However, this study did not focus on distinguishing between healthy and unhealthy individuals of the same species.

Teixeira et al. [14] investigated issues related to dataset characteristics in automated biological recognition systems used in agricultural settings. The experiment determined how background complexity, lighting variation, and environmental noise affected the transfer learning model. These findings showed that specialized preprocessing methods are required for organisms such as earthworms, which tend to be lost in earthy masses. Nevertheless, there is no standardized multi-environment dataset specifically created to monitor the health of earthworms.

Hasan et al. [15] suggested that a convolutional neural network can be used in agricultural systems to monitor the health of mobile devices using transfer learning. The architecture comparison methodology used InceptionV3 and MobileNetV2, and the efficiency and classification accuracy were measured. The experimental findings showed that MobileNetV2 offers the optimal trade-off between computational efficiency and predictive accuracy for deploying edge models in real time. However, this method has not been confirmed to detect organisms that are partially crushed by the soil or are in dark environments, such as in vermicomposting.

Chen et al. [16] examined the performance of ResNeXt-50 with CutMix data augmentation in biological classification tasks, utilizing transfer learning to overcome variability in complex invertebrate data. The experimental results revealed that sophisticated augmentation strategies have a significant positive effect on the model's robustness in specialized biological domains. However, the model has not been tested for its ability to detect long, low-textured structures in the bodies of unhealthy earthworms.

Goncalves et al. [17] applied the SSD ResNet50 architecture to detect small biological organisms using a mobile setup. The methodology aimed to optimize object detection performance for deployment on low-power mobile hardware platforms. The system had per-class rates of between 82% and 99% on a general biological subject. The model's sensitivity to changes in the body slenderness ratio of earthworms across various health conditions has yet to be tested.

Liu et al. [18] proposed the Multi-Scale Feature Fusion Network for recognizing and monitoring soil biota. The architecture has global structural properties with local physiological characteristics to enhance classification performance. Experimental findings revealed better detection of fine-grained biological characteristics in soil fauna. Nevertheless, the specific implementation of a feature fusion method for recognizing signs of earthworm death or necrotic tissue formations has not yet been studied.

Zafar et al. [19] proposed a modified earthworm optimization (MEWO) algorithm combined with deep learning for recognition tasks. The methodology used GoogleNet to extract features and the MEWO algorithm to optimize the hyperparameters. The proposed framework achieved 98.91% accuracy across all general recognition tasks. The algorithm showed good performance, but has not been directly applied to datasets assessing earthworm health status.

Gupta et al. [20] applied machine learning to investigate the functions of earthworms and soil biota on the multifunctionality of an ecosystem. The methodology was an ecological study of long-term data on earthworms, which focused on earthworms and soil ecosystem stability. The findings revealed that a healthy population of earthworms is essential for maintaining fertile soil and delivering ecosystem services. Nevertheless, this research was mainly based on population-level studies and failed to adopt real-time vision systems capable of detecting the health conditions of specific organisms.

There is a dearth of studies on the automated assessment of the health state of individual earthworms, even though artificial intelligence and machine learning techniques have been employed in previous studies to detect earthworms, classify species, monitor soil, and analyze behavior. Most approaches rely on handcrafted methods, laboratory-controlled datasets, or environmental sensor data, thereby restricting their applicability in natural vermicomposting systems. In addition, most studies focus on species recognition or large-scale population analysis rather than identifying healthy and unhealthy worms using morphological and visual features. In addition, it has not been adequately investigated how transfer learning and attention-based deep learning architectures can be used to classify the health of earthworms.

III. METHODOLOGY

A block diagram of the system is shown in Fig. 1. The proposed framework comprises image acquisition, image preprocessing, data augmentation, DL-based classification, and performance evaluation. The objective of the system is to automatically assess both earthworm health and vermicompost quality using deep learning techniques based on images.

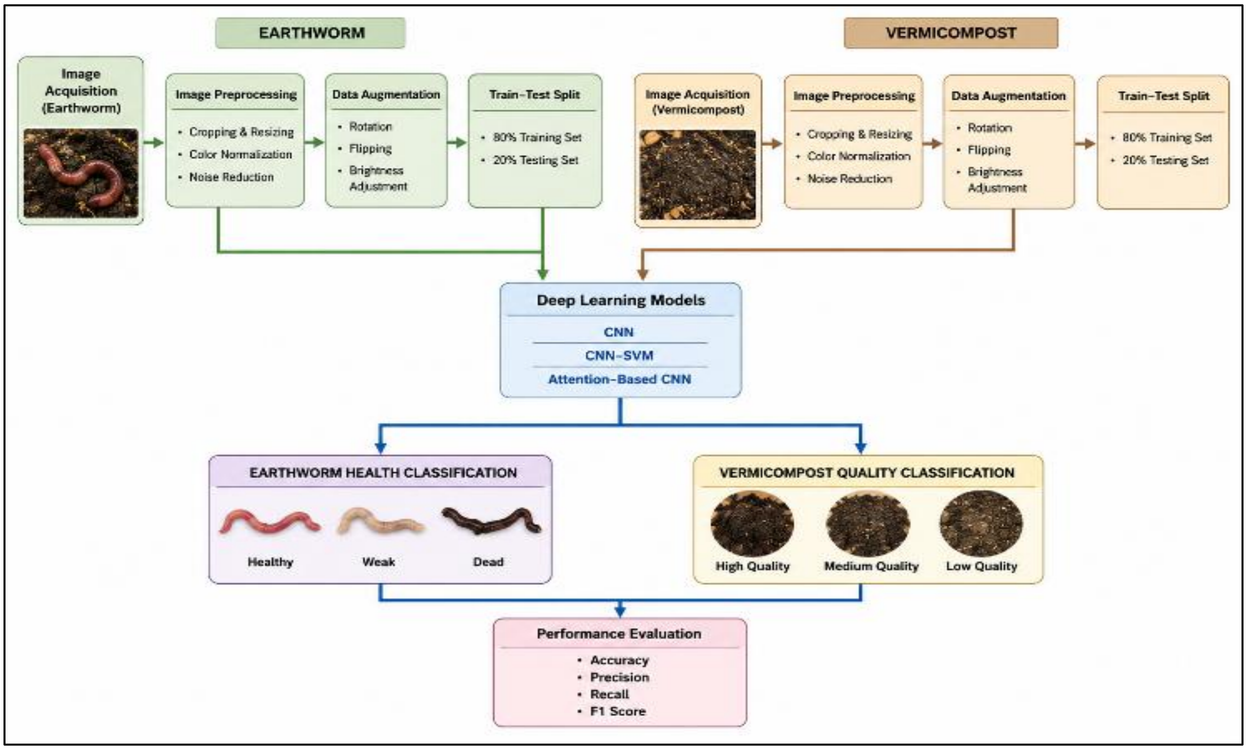


Fig. 1.Block diagram of the earthworm health and vermicompost quality recognition

A. Image Acquisition from Vermicompost Farm

The first stage of the proposed system involves collecting images of earthworms and vermicompost samples from a natural vermicomposting farm. This dataset was created using actual environmental conditions in which earthworms decompose organic waste, such as agricultural residues, vegetable waste, and plant parts. These photos were taken with a digital camera and a smartphone under different lighting conditions to provide a diverse, realistic picture of the environment for vermicomposting. This data set includes both healthy and unhealthy earthworms and vermicompost of good and poor quality. The physical appearance of healthy earthworms is well-formed, uniform in color, and smooth. In contrast, that of unhealthy earthworms shows physical defects such as discoloration, reduced size, lesions, and distorted form. Likewise, the same approach was used to categorize the vermicomposts based on their physical appearance, including color, texture, moisture level, and degree of decomposition. The images have been verified and labeled by vermiculture specialists for consistency and accuracy in the dataset creation process. Blurry and low-quality images were discarded before creating the dataset.

B. Image preprocessing

Image pre-processing plays a vital role in the designed system due to noise, complex soil backgrounds, and additional elements such as organic matter, rocks, or compost pieces in images captured from vermicomposting farms. These unwanted elements may cause the machine learning model to operate ineffectively by adding unnecessary information. Image pre-processing improves image quality and makes it easier to extract and classify features. In the first phase of image pre-processing, image cropping is performed to remove the unnecessary portion of the input image. This is done to concentrate the machine learning model on the region of interest (ROI).

The second step involved resizing the scaled images to a size acceptable to the deep learning models. The image size was standardized to ensure consistent datasets and make computation during training easier.

Moreover, the sizes of all images used in the experiment were standardized to resolutions compatible with the convolutional neural network architecture. This kind of preprocessing helped improve the performance of deep learning algorithms for feature extraction in classification.

C. Data Augmentation

The size and variability of the training set are boosted by using data augmentation, which boosts the performance and ability of the deep learning algorithms to generalize. Since data related to earthworm images may be limited and collected across varying environmental settings, the data is augmented using methods to generate new images, making it easier for the algorithm to detect strong features. This ensures that overfitting is minimized during training while allowing the algorithm to generate powerful features. The suggested model employs various augmentation methods on the training images. They include rotation, which changes the orientation of the earthworm images; flipping, which is done vertically to create a mirrored image; and brightness adjustments. Moreover, zooming is introduced, and the form is slightly altered, resulting in slight positional variations. The samples are repeated many times to generate multiple augmented samples of the original image, thereby increasing data diversity. This increases the model's capacity to detect earthworms across different orientations and light levels, thereby improving its ability to distinguish healthy from unhealthy earthworms.

D. Deep Learning Models

Three approaches to deep learning were used within the proposed network: a convolutional neural network (CNN), an SVM, and an attention-based CNN to properly classify healthy and unhealthy earthworms. The selection of these models was done to approximate the performance of deep feature extraction and advanced classification models in identifying subtle morphological differences between healthy and unhealthy earthworms.

a) convolutional neural network (CNN): This neural network architecture has historically been used for image categorization and pattern identification. CNNs can be applied to hierarchical spatial information, e.g., edges, textures, shapes, and color patterns, in images without manual feature engineering.

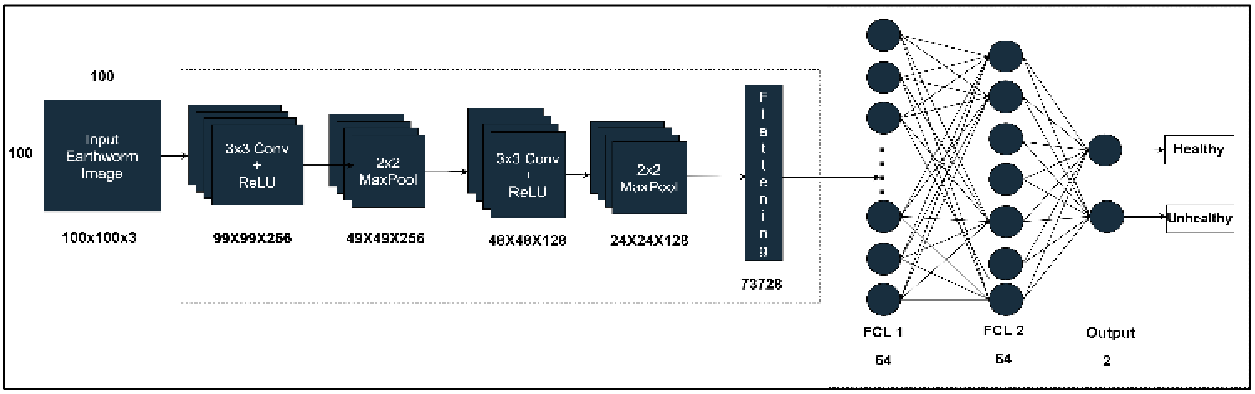


Fig. 2. Architecture of the CNN algorithm for earthworm health recognition

The study describes a CNN architecture comprising fully connected, pooling, and convolutional layers. Convolutional characteristics related to earthworm form and texture patterns are produced by the convolutional layers using discriminative features learned from filters applied to input images. The convolutional operations on the individual level generate the feature maps, which indicate important visual variables, which as body parts, surface texture, and differences in shape.

After the convolution layers, which preserve important information, there are pooling layers, which suggest that the spatial dimensionality of the feature maps is reduced. This method reduces processing complexity and lessens the network's susceptibility to small variations in input images. After that, fully linked layers get the collected features and use them for categorization and high-level reasoning. The last layer determines if the input image shows a healthy or diseased earthworm using a Softmax activation function. By using backpropagation to minimize the classification loss, the CNN model learns to identify the optimal feature representations during training.

b) CNN-SVM: The CNN-SVM hybrid model is a hybrid of CNN and the SVM in terms of feature extraction and classification, respectively. In this method, the CNN is often used as a powerful feature extractor rather than as a direct classifier.

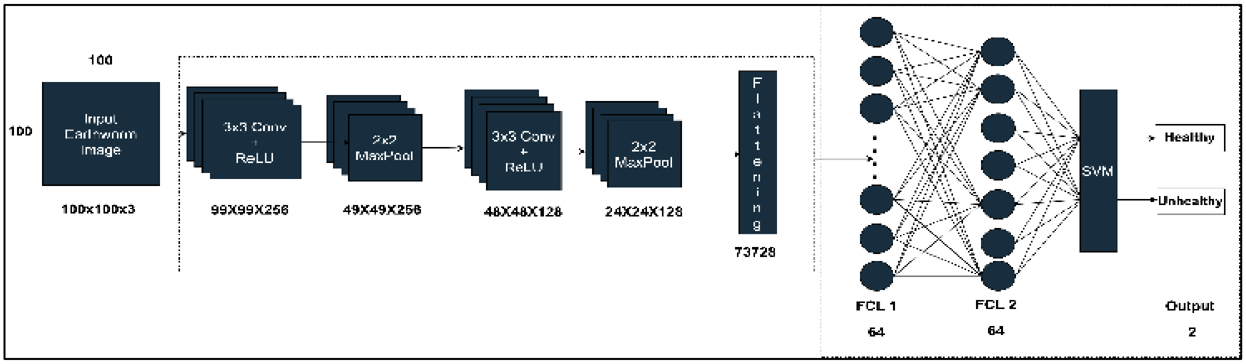


Fig. 3. Architecture of the CNN-SVM algorithm for earthworm health recognition

First, the raw images are processed by the CNN's convolutional and pooling layers, which automatically identify informative visual features of the earthworms, including their shape, color, and texture. The extracted feature vectors are fed directly into the SVM classifier, rather than into a fully connected classification layer. A supervised machine learning technique called an SVM finds the best decision boundary (hyperplane) to divide several groups. SVMs work best with small datasets in high-dimensional feature spaces. This is because the SVM optimally separates the two categories, thereby increasing accuracy and minimizing classification errors. Through CNN and SVM together, the model can benefit from automatic feature learning and accurate classification, which helps enhance its effectiveness in identifying the healthy and unhealthy earthworms.

c) Proposed attention-based CNN: An attention-based CNN enhances the basic CNN structure by incorporating an attention mechanism that allows the model to focus on the most important aspects of an input image. When examining biologically connected photos, certain parts are more important for classification than others.

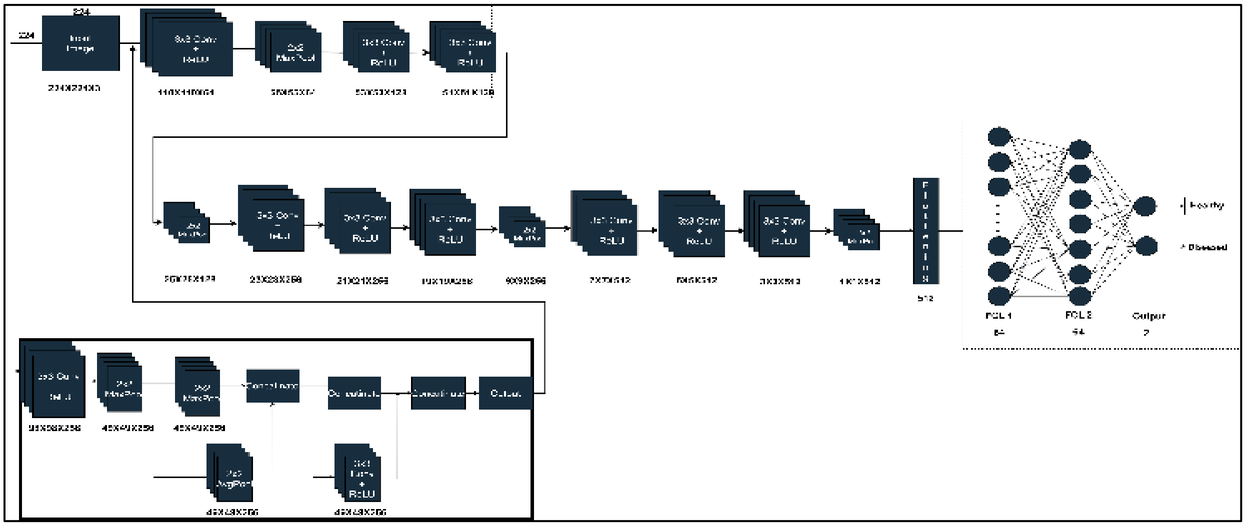


Fig. 4. Architecture of the Attention-based CNN algorithm for earthworm health recognition

Body texture, color changes, shrinkage, or lesions are specific features in earthworm health assessment that can signal unhealthy conditions. The attention mechanism helps the network highlight important areas and minimize the effects of irrelevant background elements, such as soil or organic waste. The attention module uses the feature map weights, allowing the model to place more importance on informative features during learning. This enhanced level of concentration brings better features and more capability to the model of detecting finer morphological variations between healthy and unhealthy worms. As a result, the CNN-based attention achieves better classification, especially when the backgrounds and variations in worm images are much more complex, as in vermicomposting environments.

E. Model Evaluation

The performance of the proposed deep learning models was measured using conventional machine learning and image classification criteria. These tests evaluate the model's ability to differentiate healthy and unhealthy earthworms in the test sample. Accuracy, precision, recall, and the F1-score were used to evaluate performance using the confusion matrix. The confusion matrix consists of four basic elements: true positive (TP), true negative (TN), false positive (FP), and false negative (FN). In this scenario, TP and TN denote the proper identification of unhealthy and healthy earthworms, respectively, whereas FP and FN represent the inaccurate identification of healthy and unhealthy earthworms. When combined, these metrics provide a comprehensive evaluation of the model's ability to classify the given parameters.

- Accuracy measures the overall model performance in that it is used to establish how many instances have been correctly classified out of the total number of samples.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \qquad (1)$$

- Precision evaluates the reliability of the model in predicting unhealthy earthworms.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \qquad (2)$$

- Recall measures the ability of a model to identify all unhealthy earthworms correctly.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \qquad (3)$$

- The F1-score is the harmonic mean of precision and recall, providing a fair assessment of the model's performance.

$$\text{F1} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision+Recall}} \qquad (4)$$

These assessment measures can be used to provide a more comprehensive evaluation of the CNN, CNN-SVM, and attention-based CNN models and to determine the optimal approach for automated earthworm health identification.

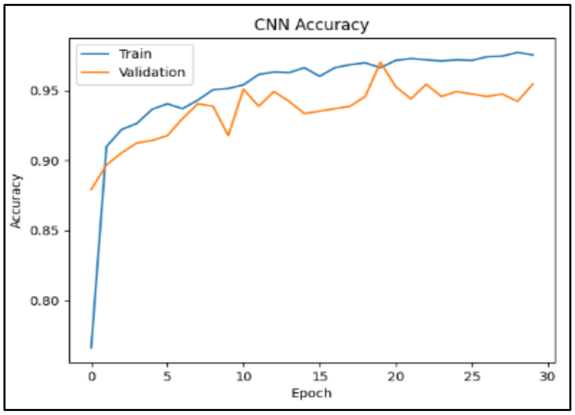
IV. RESULTS AND DISCUSSION

This section presents the experimental results obtained with the proposed deep learning models for classifying earthworm health and vermicompost quality. Three deep learning architectures, namely CNN, CNN-SVM, and ABCNN, were evaluated on the prepared dataset consisting of healthy and unhealthy earthworms as well as high-quality and low-quality vermicompost samples. The results of the experiment are shown in the table below, providing a detailed comparison of the three models and demonstrating the efficiency of the developed Attention-Based CNN model. The results of the experiment show that using an attention mechanism increases models' ability to recognize features in earthworm and vermicompost images, thereby improving classification performance.

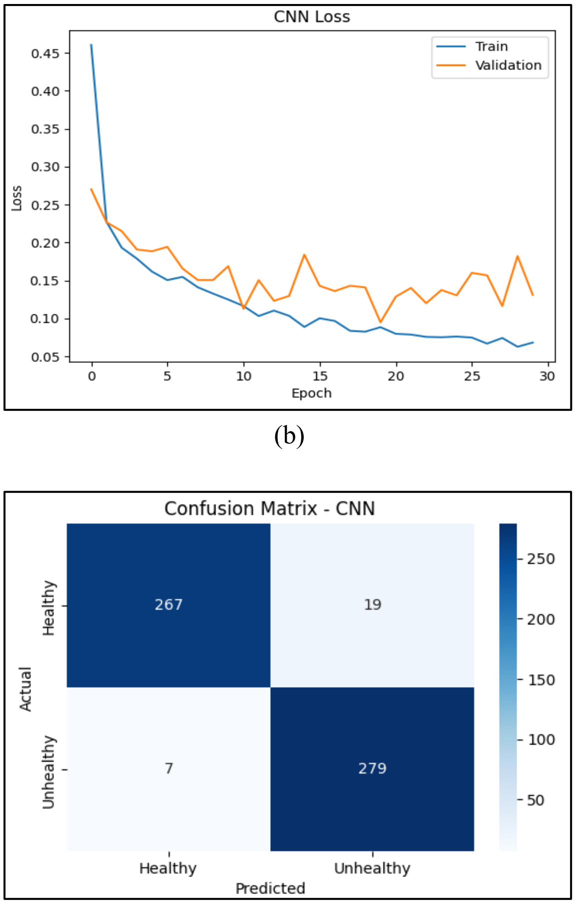
A. Result of Earthworm Health Recognition

1) Results of CNN algorithms

Fig. 5 illustrates the performance of the CNN algorithm for the classification of healthy and unhealthy earthworms.



(a)



(b)

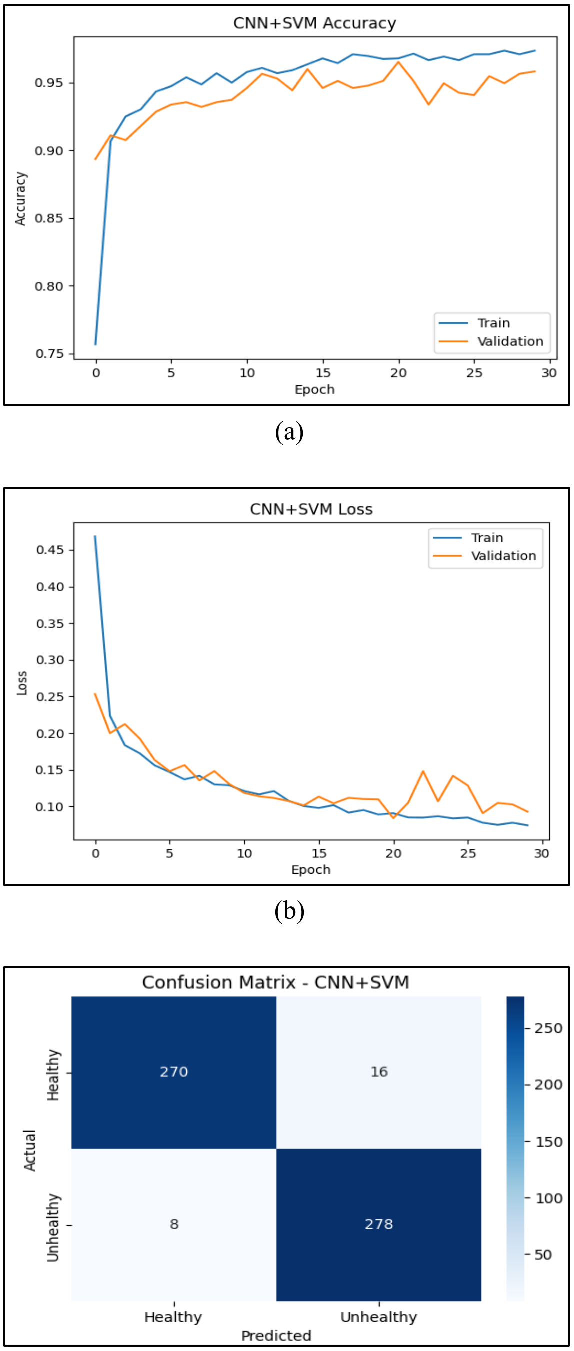
(c)

Fig. 5. Result of CNN algorithm for classification of earthworms (a) Accuracy, (b) loss, (c) Confusion matrix

Fig. 5 shows how the CNN algorithm performs in classifying healthy and unhealthy earthworms. The accuracy curve is presented in Fig. 5 (a), where the model has an overall classification accuracy of 95.45%, which implies that the CNN can learn discriminative features of the earthworm images in the process of training. Fig. 5 (b) shows a loss curve that declines as training proceeds, indicating that the model reduces classification error and converges to a fixed point. Fig. 5(c) depicts a confusion matrix, which gives a detailed description of the classification results. The table shows that most healthy and unhealthy earthworm samples are correctly identified, while a few are misidentified. A CNN model with an image-based feature set distinguished healthy from unhealthy earthworms with a precision of 0.96, a recall of 0.95, and an F1-score of 0.95.

2) Results of CNN-SVM algorithms

Fig. 6 shows the CNN-SVM algorithm outcome of the healthy and unhealthy earthworms' classification.



(a)

(b)

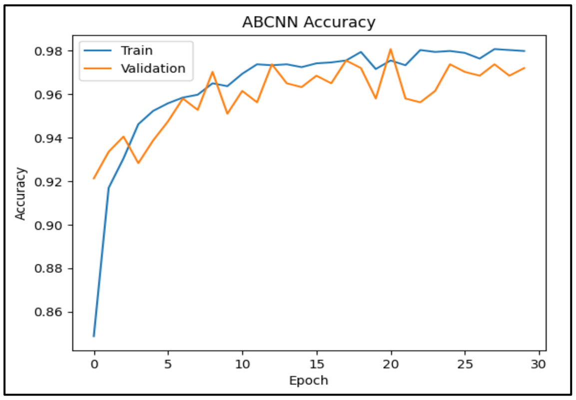
(c)

Fig. 6. Result of CNN-SVM algorithm for classification of earthworms (a) Accuracy, (b) loss, (c) Confusion matrix

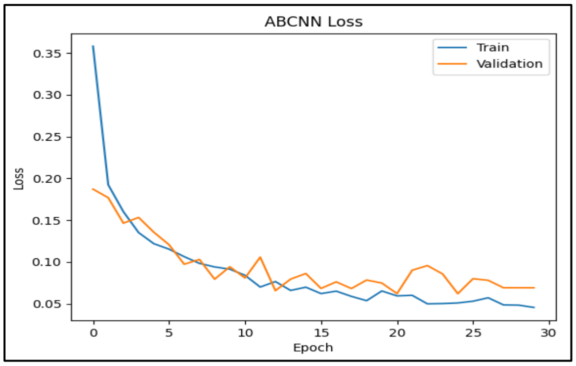
Fig. 6 (a) illustrates the accuracy curve, in which the model has an average accuracy of 95.80, which is better than the standard CNN model. The progressive improvement in training accuracy indicates that the CNN can extract meaningful features, which the SVM then classifies. Fig. 6(b) shows the loss curve, which decreases steadily as training progresses, indicating that the model successfully reduces prediction error and attains stable learning. Fig. 6(c) depicts the confusion matrix, which provides a closer look at the classification of healthy and unhealthy earthworms. Most samples are correctly classified, and there are fewer misclassifications than with the CNN model, as indicated by the matrix. The CNNSVM model had a precision of 0.96, a recall of 0.96, and an F1-score of 0.96, which proves the model to be effective in enhancing the performance of classifications to identify the health condition of earthworms.

3) Results of Attention-based CNN algorithms

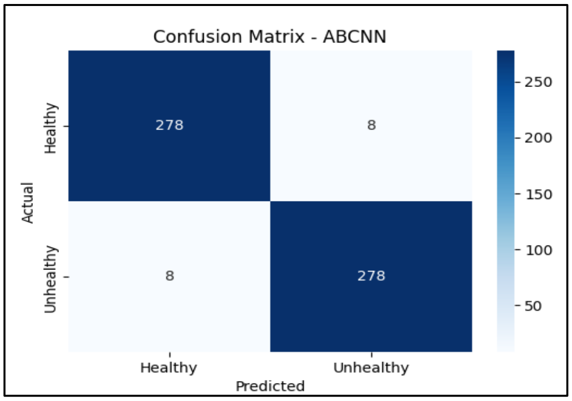
The results of the proposed Attention-Based CNN (ABCNN) algorithm of healthy and unhealthy earthworms' classification are shown in Fig. 7.



(a)



(b)



(c)

Fig. 7. Result of Proposed Attention-based CNN algorithm for classification of earthworms (a) Accuracy, (b) loss, (c) Confusion matrix

Fig. 7(a) shows the accuracy curve where the model has the maximum classification accuracy of 97.20%, which shows that the attention mechanism enhances the learning ability of the CNN by concentrating on the significant part of earthworm images. The loss curve, as illustrated in Fig. 7(b), declines gradually throughout training, indicating that the model effectively reduces classification errors and converges to a steady state. The confusion matrix is illustrated in Fig. 7(c), providing a close-up view of the classification outcomes for healthy and unhealthy earthworms. This is because the matrix shows that most samples are correctly classified, and the misclassifications are much lower than those of the other models. The accuracy of the proposed model was 0.97, recall 0.97, and F1-score 0.97, which verified that the attention-based CNN is better in automated earthworm health recognition.

4) Comparative analysis

The results of the applied deep learning models are presented in Table I, which compares the classification of healthy and unhealthy earthworms.

Table I Comparative analysis of the performance of the DL algorithms for Earthworm quality recognition

Classifiers	Precision	Recall	F1-Score	Accuracy
CNN	0.96	0.95	0.95	0.9545
CNN-SVM	0.96	0.96	0.96	0.9580
Proposed ABCNN	0.97	0.97	0.97	0.9720

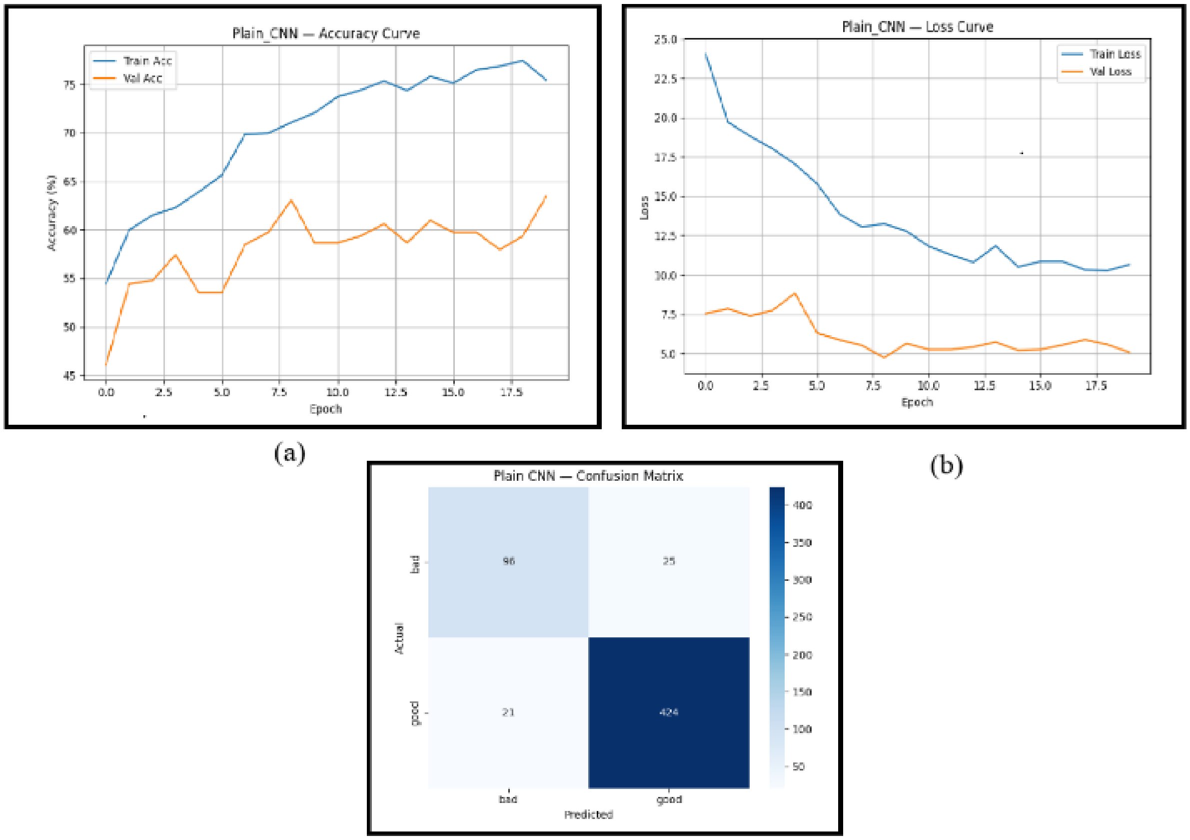
The CNN model had a precision of 0.96, a recall of 0.95, and an F1-score of 0.95, leading to a total accuracy of 95.45, which is the highest among the baseline models. These findings demonstrate that the CNN model can successfully identify basic geographical features in images. The CNN-SVM hybrid model was slightly better, achieving 0.96 in precision, recall, and F1-score, as well as 95.80% accuracy. This implies that employing CNN-based feature extraction with an SVM classifier can improve overall classification performance.

The best results were observed with the proposed Attention-Based CNN (ABCNN) model, achieving a precision, recall, and F1-score of 0.97, and a total accuracy of 97.20%. The attention mechanism may have been the cause for the superior performance, as it helps the network to focus on the key features of earthworms and their differences in morphology linked to different states of health. The findings demonstrate that the ABCNN model outperforms both approaches and that the architecture is reliable and valid for recognizing earthworm health.

B. Results of Vermicompost Quality Recognition

This section presents the results of experiments on classifying vermicompost quality using deep learning-based approaches. This is because the main aim of this research was to classify vermicompost samples into high- and low-quality categories automatically. This was done based on parameters such as the vermicompost sample's texture, color distribution, decomposition, and homogeneity. This analysis used CNN, CNN-SVM, and ABCNN methods.

1) Results of CNN Algorithm



(a)

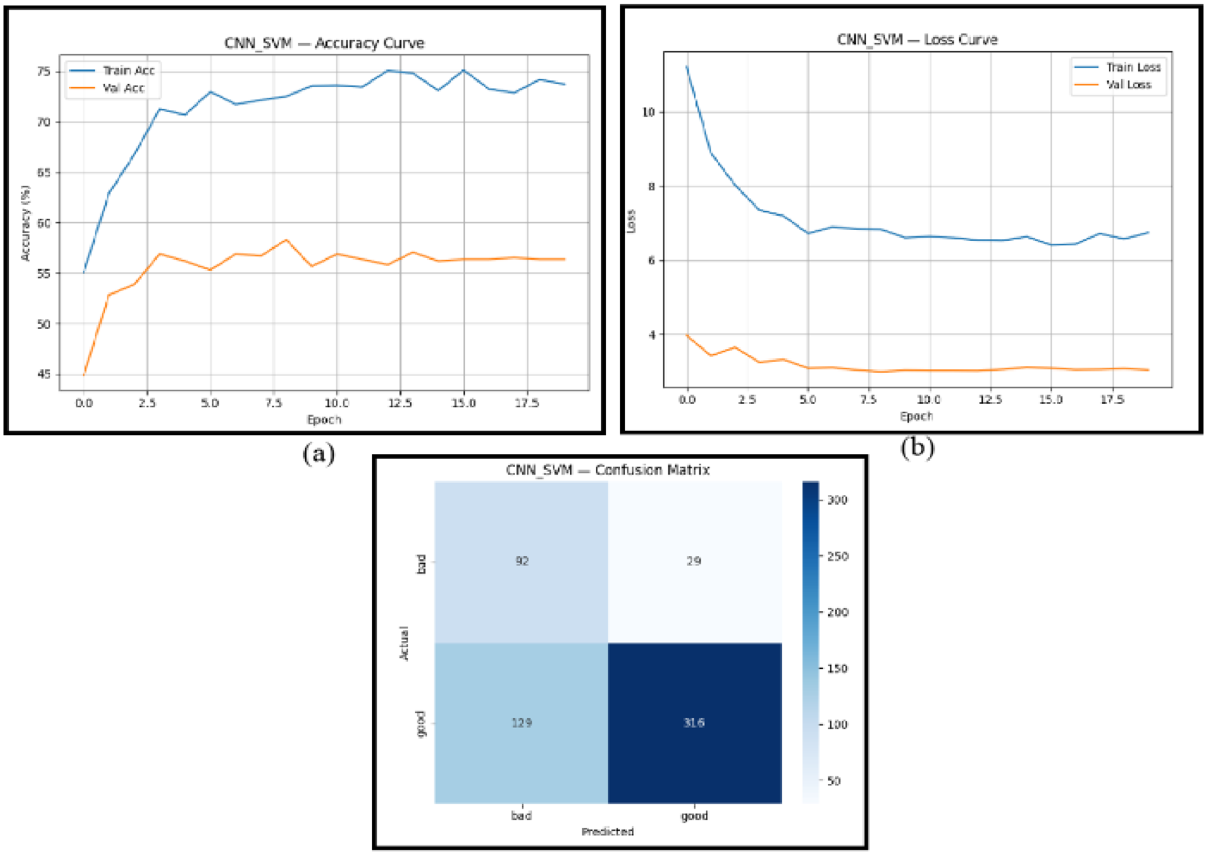
(b)

(c)

Fig. 8. Result of CNN algorithm for Vermicompost Quality Recognition (a) Accuracy, (b) loss, (c) Confusion matrix

As shown in Fig. 8(a), the classification accuracy of the vermicompost quality through the CNN model is depicted. Training accuracy increased gradually from about 55% to 76%, and validation accuracy from 46% to 63%. Thus, we could see that the model learned the discriminative features of vermicompost well from the dataset. Nevertheless, there is a difference between training and validation accuracy, which means that there is some overfitting issue. From the loss curve, we see that both the training and validation losses decreased from 24 and 7.5 to 10 and nearly 5, respectively. Thus, it showed that the model could converge well and obtain stable performance by training. Furthermore, from the confusion matrix, we see that the model correctly classified 96 samples as bad-quality vermicompost's and 424 as good-quality vermicomposts, with only 25 bad-quality samples misclassified as good-quality and vice versa.

2) Results of CNN-SVM Algorithm



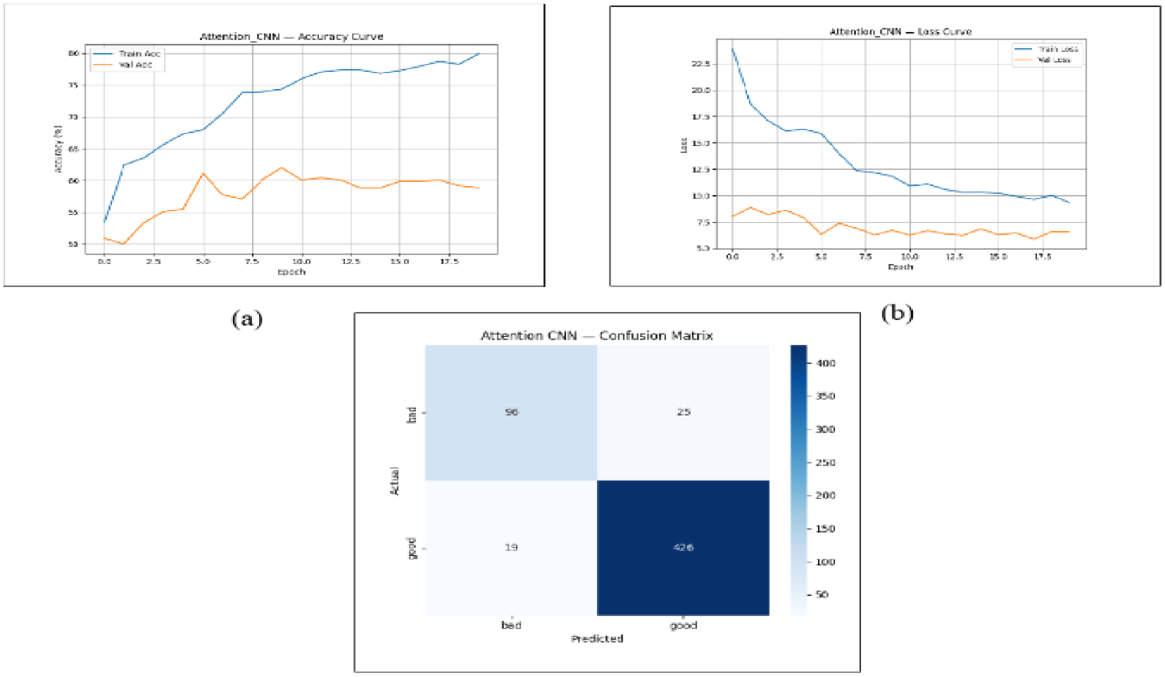
(a) (b)

(c)

Fig. 9. Result of CNN-SVM algorithm for Vermicompost Quality Recognition (a) Accuracy, (b) loss, (c) Confusion matrix

The performance of the CNN-SVM approach is illustrated in Fig. 9. A rise in the training accuracy level is noticed between approximately 55% and 74%, which signifies the efficient operation of the feature extraction part, followed by successful classification of features through the use of the SVM layer. Meanwhile, only a slight increase in validation accuracy was observed, from 45% to 57%. Furthermore, apparent reductions in losses are evident in the plots: the training losses decreased from around 11.2 to 6.7, while the validation losses reached 3.0. In the confusion matrix, the hybrid approach correctly classified 92 bad-quality samples and 316 good-quality samples. In comparison, 29 low-quality samples and 129 high-quality samples were misclassified as low- and high-quality, respectively. Though the CNN-SVM model achieved satisfactory results during training, its discriminatory capacity against high-quality samples should be improved.

3) Results of the Attention-Based CNN Algorithm



(a) (b) (c)

Fig. 10. Result of Attention-based CNN algorithm for Vermicompost Quality Recognition (a) Accuracy, (b) loss, (c) Confusion matrix

The outcomes of the proposed Attention-Based CNN (ABCNN) model for quality recognition of vermicompost's are shown in Fig. 10. As observed from the accuracy plot, the training accuracy increases from approximately 53% to 80%. In contrast, validation accuracy increases from 51% to almost 60%, indicating effective discrimination of vermicompost features via attention. While there is a considerable discrepancy between the training and validation accuracies, the latter remains fairly stable throughout training. The decreasing trend in loss is evident during training, with values falling from about 24 to less than 10. On the other hand, the loss of validation reduces from about 8.0 to 6.5 and stabilizes thereafter. The confusion matrix indicates high classification performance: 96 bad-quality samples are correctly classified, and 426 good-quality samples are correctly recognized, with only 25 misclassifications for bad samples and 19 for good ones. Compared with the CNN and CNN-SVM models, the presented model produces lower classification errors and higher recognition accuracy due to its efficient attention mechanism.

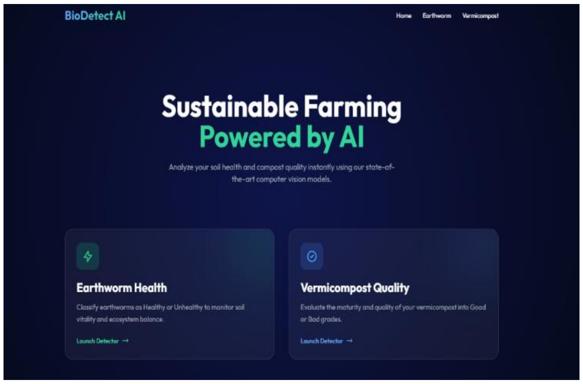
4) Comparative Analysis

Table II Comparative Performance Analysis of Deep Learning Models for Vermicompost Quality Recognition

Classifiers	Precision	Recall	F1-Score	Accuracy
CNN	0.87	0.85	0.86	85.71
CNN-SVM	0.89	0.88	0.88	88.00
Proposed ABCNN	0.91	0.90	0.90	90.95

From Table II, it is evident that all three DL approaches accurately classified vermicompost quality samples. The CNN achieved 85.71% accuracy, indicating its ability to extract relevant color and texture information from vermicompost images. The CNN-SVM approach improved classification accuracy to 88.00% by combining a CNN for feature extraction with SVM classification. The best results were achieved with the proposed attention-based CNN (ABCNN), yielding a precision of 0.91, recall of 0.90, F1-score of 0.90, and accuracy of 90.95%. ABCNN outperformed the other two methods because it uses an attention mechanism that allows the neural network to focus on informative regions of compost textures, patterns, and colors.

The web application is developed for this system and tests the earthworms and the vermicompost quality. The results displayed in the web application are shown in Fig. 11.

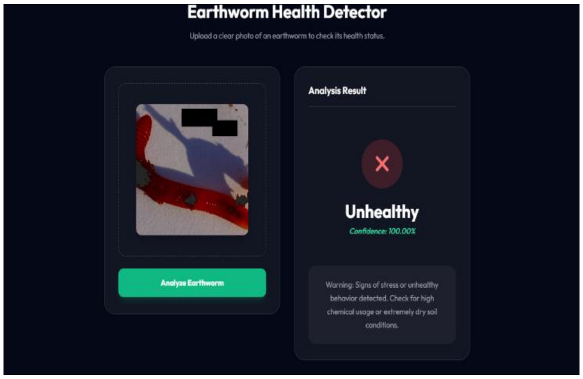


Analyze your soil health and compost quality instantly using our state-of-the-art computer vision models.

Classify earthworms as Healthy or Unhealthy to monitor soil vitality and ecosystem balance.

Evaluate the maturity and quality of your vermicompost into Good or Bad grades.

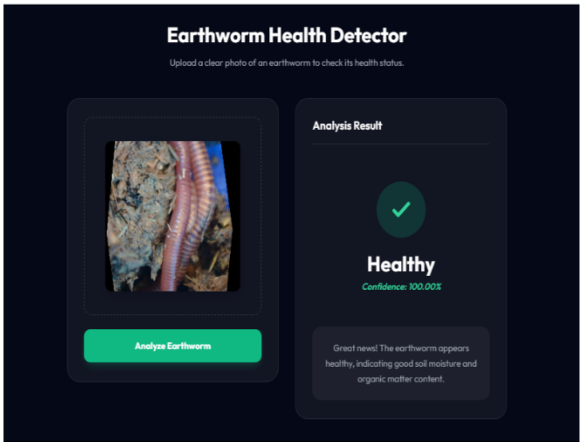
(a)


[redacted]

Upload a clear photo of an earthworm to check its health status.

Warning: Signs of stress or unhealthy behavior detected. Check for high chemical usage or extremely dry soil conditions.

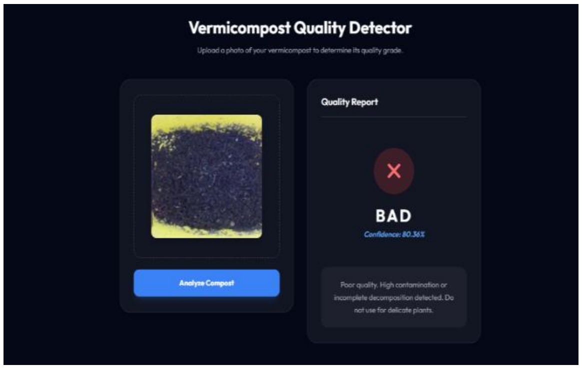
(b)



Upload a clear photo of an earthworm to check its health status.

Great news! The earthworm appears healthy, indicating good soil moisture and organic matter content.

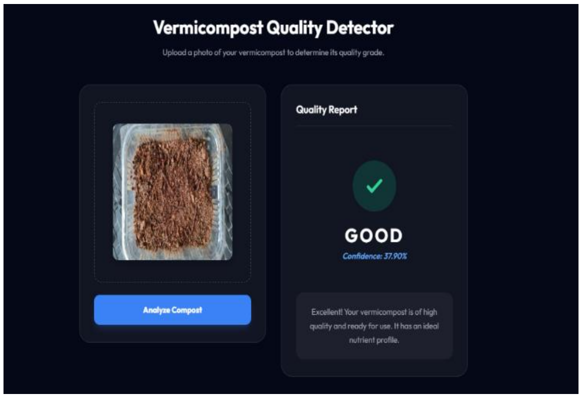
(c)



Upload a photo of your vermicompost to determine its quality grade.

Poor quality. High contamination or incomplete decomposition detected. Do not use for delicate plants.

(d)



Upload a photo of your vermicompost to determine its quality grade.

Excellent! Your vermicompost is of high quality and ready for use. It has an ideal nutrient profile.

(e)

Fig. 11. Results on webpage (a) Main page of the web application (b) Recognition of unhealthy earthworm (c) Recognition of healthy earthworm (d) Recognition of bad quality vermicompost (e) Recognition of bad quality vermicompost

V. CONCLUSION

In this paper, a deep learning technique was applied to differentiate healthy from unhealthy earthworms in a vermicomposting setting. The CNN, CNNSVM, and ABCNN models were used to analyze a set of images consisting of 2,860 earthworms, which were obtained in a farm producing vermiculite pots. The quality of the obtained pictures could be improved by applying multiple image preprocessing and data augmentation techniques to enhance classification accuracy. The main results of the experiment demonstrated that all three tested models achieved relatively high classification accuracy for the analyzed earthworm conditions. While the CNN algorithm achieved 95.45% accuracy, the hybrid CNNSVM algorithm performed slightly better, achieving 95.80% accuracy. As expected, the proposed Attention-Based CNN model produced even higher results, achieving an accuracy of 97.20%. Such an improvement can be explained by the model's attention mechanism, which enables it to focus on the essential features of the body structure, texture, and color changes in earthworms. Overall, the suggested solution is a highly relevant tool for managing earthworm health.

Future research can increase the dataset by including more diverse images from various composting conditions of vermiculite to improve the performance of the proposed algorithm. Additionally, the proposed system can be integrated into IoT-based sensing systems or apps to enable real-time analysis of earthworm condition in farms. Moreover, advanced deep learning and lightweight models can also be used for such applications.

REFERENCES

[1] G. K. Meghwanshi, "Review on AI-Based Recognition of Earthworm Health," *Int. J. Innov. Res. Technol.*, vol. 12, no. 6, 2024.

[2] S. Andleeb *et al.*, "ESIDE: A Method to Identify Earthworm Species," *PLOS ONE*, vol. 16, no. 9, 2021.

[3] T. Çelik and H. Uguz, "Deep Learning-Based System for Real-Time Detection of Earthworm Cocoons," *ResearchGate*, 2022.

[4] K. Kavitha *et al.*, "Earthworm Classification via NGS and Neural Networks," *Applied Sciences*, vol. 15, no. 12, 2025.

[5] X. Wang *et al.*, "Earthworms and Nitrous Oxide Emissions: A Global Meta-Analysis," *Science of the Total Environment*, 2024.

[6] Ramazanoglu, "Thermal Imaging for Soil Health," *Soil Biology and Biochemistry*, 2024.

[7] Kumar *et al.*, "Role of Earthworms in Alleviating Soil Compaction," *Arabian Journal of Geosciences*, 2024.

[8] E. Ayintareba *et al.*, "Application of Transfer Learning in Image Classification," *Asian Journal of Research in Computer Science*, 2025.

[9] Djerdj *et al.*, "Movement Behavior as a Proxy for Health," *Frontiers in Environmental Science*, 2022.

[10] Ibrahim *et al.*, "IoT-Based Environmental Control System," in *Proc. IEEE Conf.*, 2025.

[11] Li *et al.*, "CenWholeNet for Anchor-Free Detection," *Machine Learning Research*, 2025.

[12] M. F. Tsai *et al.*, "Time-Series Feature Extraction for Transfer Learning," *International Journal of Research and Applied Science (IJRAS)*, 2025.

[13] T. T. Nguyen *et al.*, "Efficient Model of Deep Learning to Classify Insects," *ResearchGate*, 2025.

[14] C. Teixeira *et al.*, "Challenges in Dataset Characteristics for Bio-Recognition," *Agricultural Informatics*, 2025.

[15] Hasan *et al.*, "Mobile-Based Health Monitoring in Agriculture," in *Deep Learning in Agriculture*. 2021.

[16] Li *et al.*, "Transfer Learning CNN to Detect Insects," *IP102 Dataset Analysis*, 2025.

[17] J. Gonçalves *et al.*, "SSD ResNet50 for Mobile Device Deployment," *Traps and Biological Sensors*, 2025.

[18] Liu *et al.*, "Multi-Scale Feature Fusion for Soil Biota," *Soil Science*, 2025.

[19] Zafar *et al.*, "Modified Earthworm Optimization with GoogleNet," *Computational Intelligence*, 2024.

[20] R. Gupta *et al.*, "Coordinated Actions of Earthworms for Soil Multifunctionality," *Applied Soil Ecology*, 2026.