TOWARDS ECOLOGICAL SUSTAINABILITY: HARVEST PREDICTION IN AGRIVOLTAIC CHILI FARMING WITH CNN TRANSFER LEARNING

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ABSTRACT

Agrivoltaic systems, which integrate agricultural production with solar energy generation, present a promising approach to ecological sustainability. This study focuses on predicting chili harvests within an agrivoltaic setup using Convolutional Neural Networks (CNN) with transfer learning. Accurate yield prediction is vital for optimizing both agricultural output and energy generation. The study evaluates three pre-trained CNN models—EfficientNetV2L, EfficientNetV2M, and ResNet 50—fine-tuned with specific agrivoltaic data. The experimental setup includes a solar-powered greenhouse with IoT-controlled micro-climate management to ensure optimal growing conditions. The models were selected based on their high accuracy in Keras applications, with EfficientNetV2L and ResNet 50 achieving 100% accuracy, and EfficientNetV2M reaching 96% in chili crop counting. The results show quick convergence during training and validation, indicating effective model learning. The study also includes a life cycle analysis (LCA), confirming that using photovoltaic systems as a substitute for conventional energy sources is environmentally sustainable. Overall, this research demonstrates that CNN transfer learning is highly effective for crop counting and resource management, contributing to sustainable agrivoltaic farming and highlighting the potential of advanced AI techniques in agriculture.

Keywords: Agrivoltaic systems, Convolutional Neural Networks (CNN), Chili harvest prediction, Sustainable agriculture, Transfer learning.

تنبؤ حصاد الفلفل في الأنظمة الزراعية الفلطائية باستخدام التعلم المنقول عبر الشبكات العصبية : نحو الاستدامة البيئية الالتفافية (CNN)

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المستخلص

الأنظمة الزراعية الفلطائية، التي تدمج الإنتاج الزراعي مع توليد الطاقة الشمسية، تقدم نهجًا واعدًا لتحقيق الاستدامة البيئية .تركز هذه الدراسة على التنبؤ بمحاصيل الفلفل الحار في نظام زراعي فلطائي باستخدام الشبكات العصبية الالتفافية (CNN) مع التعلم المنقول .يُعد التنبؤ الدقيق بالإنتاج ضروريًا لتحسين كل من الإنتاج الزراعي وتوليد الطاقة .تقيم الدراسة ثلاثة نماذج CNN مدربة مسبقًا : EfficientNetV2L و EfficientNetV2M وResNet 50، والتي تم ضبطها باستخدام بيانات محددة لنظام الزراعة الفلطائية . يتضمن الإعداد التجريبي دفيئة تعمل بالطاقة الشمسية مع إدارة مناخية دقيقة يتم التحكم بها عبر إنترنت الأشياء لضمان ظروف نمو مثالية .تم اختيار النماذج بناءً على دقتها العالية في تطبيقات Keras، حيث حقق كل من EfficientNetV2L و ResNet 50 دقة بنسبة 100%، في حين بلغت دقة 96% EfficientNetV2M في عملية عد محصول الفلفل .أظهرت النتائج تقاربًا سريعًا أثناء التدريب والتحقق، مما يشير إلى فعالية تعلم النماذج .كما تتضمن الدراسة تحليل دورة الحياة (LCA)، مما يؤكد أن استخدام الأنظمة الفلطائية كبديل لمصادر الطاقة التقليدية هو أمر صديق للبيئة .بشكل عام، توضح هذه الدراسة أن التعلم المنقول باستخدام CNNفعال للغاية في عد المحاصيل وإدارة الموارد، مما يسهم في الزراعة الفلطائية المستدامة ويسلط الضوء على إمكانيات تقنيات الذكاء الاصطناعي المتقدمة في الزراعة.

الشبكات العصبية التلافيفية الكلمات المفتاحية: أنظمة الزراعة الشمسية،الزراعة المستدامة، التعلم (CNN)، توقع حصاد الفلفل الحار،

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INTRODUCTION

The agricultural sector is undergoing a transformative change that is driven by the integration of advanced technologies to setback addressed by Kamaludin et al. (22) and von Groß et al. (39). This problem is occurring not only in Indonesia but also around the world, as discussed by Edita and Dalia and Msangi et al. (12,28). Agrivoltaic farming, which integrates agricultural activities with solar energy production, is a promising practice as presented by Almaenny in 2018 (1), Mohammed in 2018 (27), Rusol and Al-Timimi in 2023 (31). By enabling the dual use of land, agrivoltaic systems offer a solution to the competing demands for agricultural land and renewable energy infrastructure. Chili farming, a staple crop in many regions, is an ideal context to explore the ecological advantages of this approach. However, optimizing yields in agrivoltaic systems presents unique challenges requiring advanced predictive techniques as presented by Oktarina et al.(29,30) Solar energy use in agriculture is consistent with the government's policy of increasing the mix of renewable energy use by 2030. Solar energy is abundant in Indonesia which is near the equator, and has tropical weather ideal for harvesting solar energy, (11,21,22,34,35). One method of incorporating technology in agriculture is to build a greenhouse, which can be adjusted according to plant needs and is pest-free, as presented by Collado et al. and Yoo et al. (7,40). Greenhouse technology can be used instead of conditioned agriculture to increase agricultural output. Smart farming can be an automatic greenhouse with a controlled climate to increase crop yield, (24,25) or the implementation of robotics, (8,9,10,36) and other automation. Agrivoltaic smart farming takes the monitoring concept a step further by incorporating advanced technologies such as Internet of Things (IoT) devices, sensors, and machine learning algorithms to optimize farming practices. This integration enables precise monitoring and management of agricultural inputs, leading to increased efficiency and sustainability. Smart agriculture integrates artificial intelligence (AI) in agricultural systems. The part of AI most suitable for predictions is neural networks through machine learning training, where farmers can estimate how much to harvest through growth predictions, Chamara et al.(5), plant disease detection, Arsenovic et al. (2), Ferentino (13), Fuentes et al. (14), Kerkech et al. (23), maturity detection, Begum et al. (4), and crop counting Chlingaryan et al. (6). Shaikh et al. (35), Attri et al. (3), and Javaid et al. (19) reviewed the method of machine learning and AI implementation in agriculture. Farming production can be predicted by a method called crop counting, which counts how many crops are detected in a plant, and from this detection, farmers can calculate the current agricultural yield (24). Crop counting is part of farm planning and management. Planning and management using AI also includes scheduling and logistics to estimate harvest yields. Chamara et al. (5) implemented deep learning CNN for crop monitoring, Chamara et al., and Li et al. (5,26) designed a strawberry R-CNN method to count strawberries. Harvest yield predictions provide helpful information for crop quality control by monitoring crop health and detecting disease symptoms early to avoid crop failure. Digital crop counting can be challenging because it requires image categorization and detection of plants that vary in shape and color. The image data taken is also greatly influenced by lighting due to weather, the angle at which the photo is taken, and the camera quality used, not to mention if branches and foliage obscure the intended crop object, Veramendi et al. (38) used SVM for maize plant counting and crop evaluation with accuracy from 0.68 to 0.85. Conventional image processing approaches based on shallow learning are insufficient for effective detection, necessitating the implementation of a Convolution Neural Network (CNN) with deep learning features that can learn image characteristics independently during the data training process, such as Zhang and Li (41) counted lettuce using YOLOv5 and Huang et al. (17) investigated the application of deep learning in crop counting. CNN has the ability to capture complex patterns and structure images, such as the varying position of crops inside an image, and it has the ability to share the convolutional layers, which reduces the number of parameters required. Big datasets are crucial for effective results, but producing big datasets takes work for farmers. Hence, one of the best features of CNN is transfer learning, which can overcome the requirement of big data by integrating small data with big datasets pre-trained by previous researchers. Transfer learning, a technique where a pre-trained model is adapted to a new but related task, presents a particularly advantageous approach for enhancing crop yield predictions. Transfer learning models are varied and assessable through Keras Application. The user-friendly library helps farmers to implement this method. Among the well-known models is EfficientNet, introduced by Tan (37) and adopted by Himel et al. (16) to identify sheep breeds in low-resolution images with an accuracy of more than 0,85 and even 1. EfficientNetV2M and EfficientNetV2L are smaller and faster variants of EfficientNet models developed by Tan and Le (37). This study proposed to develop and evaluate a CNN-based transfer learning model to predict chili harvests in an agrivoltaic system. The early hypothesize states that implementing CNN transfer learning will significantly enhance the accuracy of harvest predictions, thereby contributing to more efficient and ecologically sustainable farming practices. Our research seeks to optimize chili production and illustrate the broader potential of combining advanced AI techniques with innovative agricultural practices to promote ecological sustainability. This paper presents a comparative analysis of three transfer learning models: RestNet50, EfficientNetV2M, and EfficientNetV2L. The RestNet50 model is the earlier model developed by He et al. (15), which compares the latest EfficientNetV2 models.

MATERIAL AND METHODS

This paper discusses the broader implications of the findings for agrivoltaic farming and agricultural sustainability. This research provides a comprehensive framework for integrating AI-driven solutions into sustainable agricultural practices, paving the way for more resilient, productive, and environmentally friendly farming systems. Hence, significant improvements in crop yield prediction can be achieved by integrating the ecological benefits of agrivoltaic systems with the advanced predictive capabilities of CNN transfer learning. This synergy of technologies holds great promise for the future of sustainable agriculture, aligning food production with environmental conservation and renewable energy objectives. The potential impact of this research is far-reaching, offering a comprehensive framework for integrating AI-driven solutions into sustainable agricultural practices and paving the way for more resilient, productive, and environmentally friendly farming systems. The proposed method in this study is divided into 3 steps; agrivoltaics setting design, crop yield prediction method, and ecological assessment impact simulation.

A- **Agrivoltaic Setting Design:** This paper proposes agrivoltaics setting design in 2 form, solar powered greenhouse and without greenhouse, both methods employ automatic irrigation and fertigation system. However, the greenhouse leverages microclimate control integrated with IoT Monitoring. Modelling and Design of Micro-climate Automatic Monitoring System of a Greenhouse in Agrivoltaic Setting as presented in Fig. 1 where the system is divided into the functions and the application.

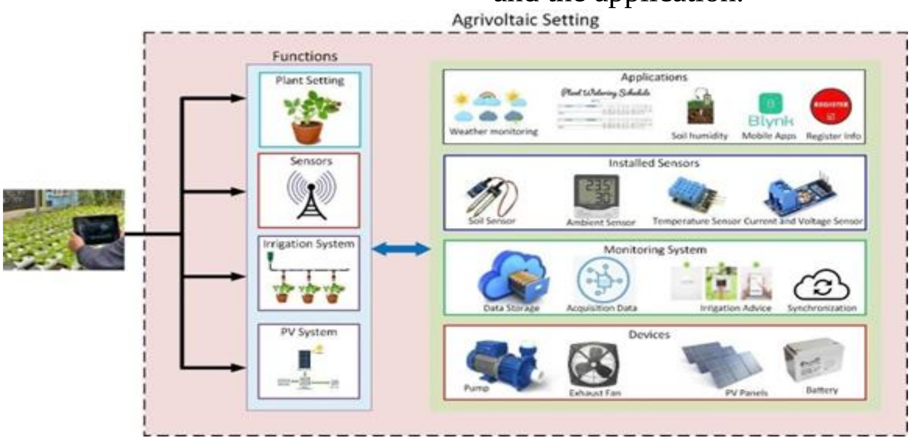


Fig 1.The proposed automatic agrivoltaic system

The IoT monitoring device records inputs from sensors installed in this agrivoltaic settings are soil sensors, ambient sensor, temperature sensor, and current and voltage sensor for PV system. The monitoring system functions as data storage, acquisition data, irrigation advice and data synchronization. This monitoring system is used to activate the devices that are pumps, exhaust fan, PV panels system, and battery. The system ensures the micro-climate system stays in ideal plant condition setting.

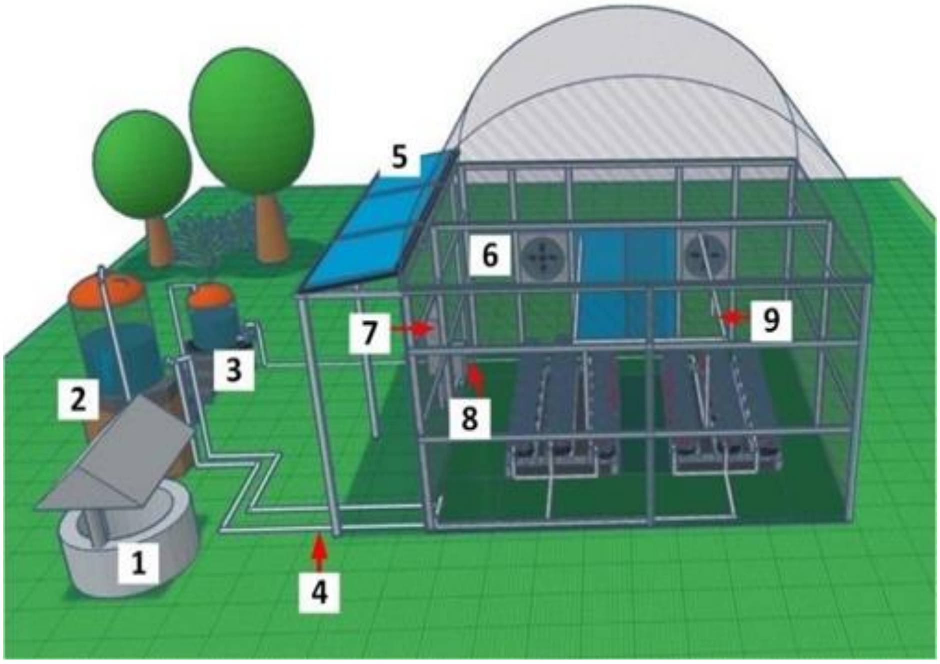


Fig 2. Automatic Agrivoltaic Setting

The Agrivoltaic setting considered in this study is given in Fig. 2. The automatic agriculture benefits from the solar energy where the micro-climate is controlled to meet the ideal environment for plants. The greenhouse system consists of (1) well, (2) irrigation system, (3) fogging system, (4) piping, (5) PV panels, (6) exhaust fan, (7) combiner box, (8) batteries, and (9) piping for fogging. Because the greenhouse is located in an area that is not served by clean water from the Regional Drinking Water Company, the well (1) is the primary water source in this greenhouse system. The irrigation system (2) responsible for automatic watering system, while fogging system (3) is required to stabilize the micro-climate inside the greenhouse. PV panels supply electricity converted from solar irradiance to power the electronics in the greenhouse (located inside the combiner box (8)). The batteries are the storage system that ensure the electricity is available during day and night, or sunny and cloudy weather. The current produced by the PV panels install on the greenhouse is given by (18)

$$\mathbf{I} = \mathbf{I_0}\left(\frac{\mathbf{qV}}{\mathbf{e^{nKT}}} - \mathbf{1}\right) - \mathbf{I_{ph}}, \qquad (1)$$

where I is the generated current by a solar cell (A), I_{ph} is light-generated current, I_0 is the initial current, V is the voltage (V), e^{nKT} is the Botzmann factor, and k is the Boltzmann constant (1.380649×10^{-23} m^2 kg s^{-1} K^{-1}). The voltage supplied to the greenhouse is (18)

$$\mathbf{V_{oc}} = \frac{\mathbf{nKT}}{\mathbf{q}}\mathbf{ln}\left(\frac{\mathbf{I_{out}}}{\mathbf{I_0}} + \mathbf{1}\right). \qquad (2)$$

The solar panel efficiency (ɳ) is defined as the comparison between power input (P_{in}) and the generated power output (P_{out}) and is given as below (19):

$$\mathbf{ɳ} = \frac{\mathbf{I_{mp}.V_{mp}}}{\mathbf{P_{in}}} \times \mathbf{100\%}. \qquad (3)$$

The heat transfer model for the agrivoltaic setting considered in this study is adopting from Ma et al. (28), taking the factors affecting greenhouse climate shown in Fig. 3. The greenhouse’s indoor micro-climate is modelled by the greenhouse's indoor temperature, relative humidity, and CO_2 concentration (27)

$$\boldsymbol{\rho_{air}c_{air}v_{air}}\frac{\mathbf{dT_{air}}}{\mathbf{d\tau}} = \mathbf{Q_{wall}} + \mathbf{Q_{soil}}, \qquad (4)$$

where ρ_{air} is the air density, c_{air} is the air heat capacity, v_{air} is the air volume inside greenhouse, T_{air} is air temperature, Q_{wall} is the heat convection between the greenhouse plastic wall and air, and Q_{soil} is the heat convection between the soil and air (28).

$$\rho_{air} c_{air} v_{air} \frac{dT_{air}}{d\tau} = h_{env} A_{env} (T_{env} - T_{air}) + h_{soil} A_{soil} (T_{soil} - T_{air}), \quad (5)$$

where T_{env} is the temperature in the envelope (greenhouse temperature), and T_{soil} is soil surface temperature. h and A are the convective heat transfer coefficient and areas (28).

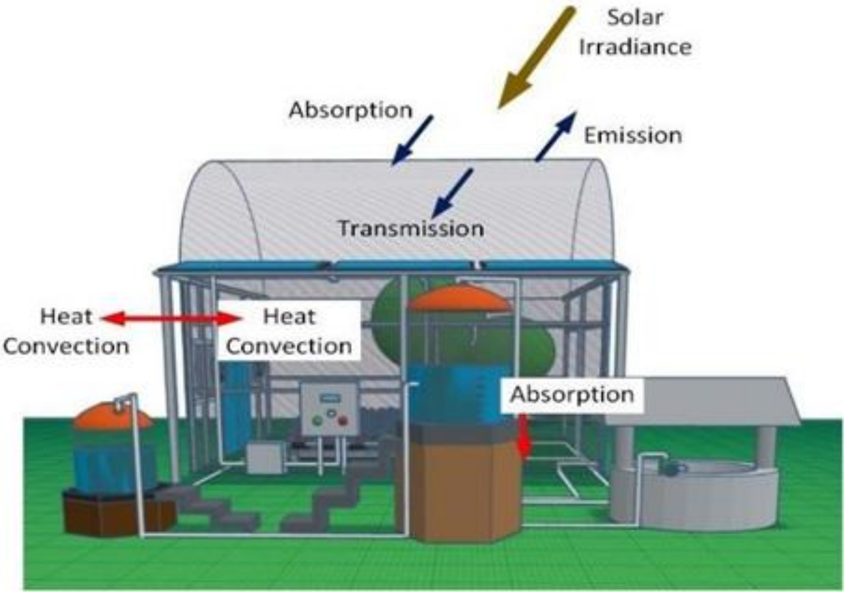


Fig 3.Heat transfer modeling in agrivoltaic setting

Fig. 4 presents the design of micro-climate automatic monitoring system where soil humidity sensor is connected to Arduino that control the activation of pump and irrigation system inside the greenhouse. The sensor-arduino system is connected to node MCU for internet connection and send to IoT interface with Node-RED application installed to farmer's electronic devices such as phone, tab, or laptop. The benefits resulted from this automatic monitoring are better crop management, possible optimum growth rate due to near ideal climate and no pest condition, real time monitoring, better prediction for decision making, optimal water consumption, prevent plants disease, possible soil nutrient preservation, reduce resources, and cleaner and more efficient agricultural process.

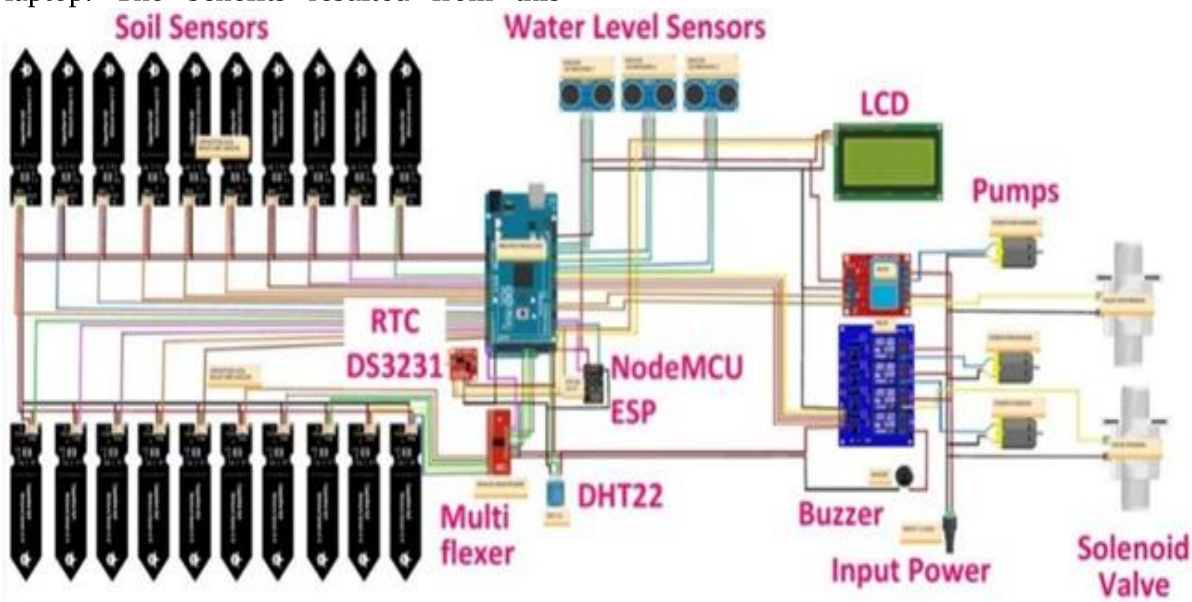


Fig. 4. Iot Monitoring Circuit Design

B- Crop Yield Prediction Method

The proposed crop yield prediction method in this study is given in Fig. 5 which implements a Convolution Neural Network (CNN) to count the chili crop and predict the harvest yield. The transfer learning features can provide a small dataset to get accurate counting and can adjust the dataset; hence, can be employed to monitor crops across large agricultural areas. Transfer learning predicts crop yields by fine-tuning a pre-trained CNN model with images and environmental data specific to chili crops. The pre-trained model's ability to recognize relevant features from the images can significantly enhance the accuracy of yield predictions, leading to better resource management and improved agricultural sustainability. Data collection and Pre-processing is shown in Fig. 5 where the dataset input to pre-trained models is from ImageNet which allows the model to learn a wide range of features, such as edges, textures, shapes, and patterns, which are useful for image recognition tasks. The transfer learning models implemented for crop counting in this study, as shown in Fig. 5, are RestNet50, EfficientNetV2M, and EfficientNetV2L. EfficientNetV2M and EfficientNetV2L are the latest EfficientNet models developed by Tan and Le in 2021, and the RestNet50 model is an earlier model developed by He et al. (15) to compare the latest EfficientNetV2 models.

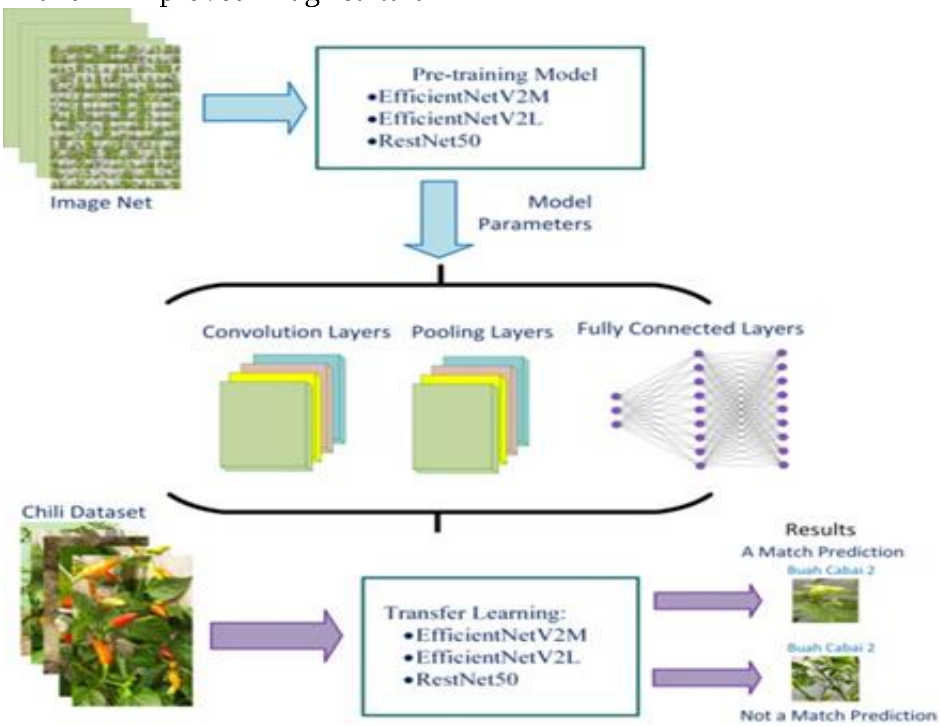


Fig. 5. The proposed CNN-transfer learning considered in this study

EfficientNetV2L and EfficientNetV2M are the developments of EfficientNet, which has smaller models, faster training, and better parameter efficiency than previous EfficientNet. The M and L are medium and large to indicate the size of model implemented; therefore, EfficientNetV2L has more parameter and computationally larger than EfficientNetV2M. EfficientNetV2M and EfficientNetV2L are more variative in model size, accuracy, and computational efficiency; hence, ideal for crop counting which involves fine-tuned image classification. RestNet50 is a model with 50 layers consisting of convolution, pooling, and fully connected layers. The main novelty of the RestNet architecture is that it uses the residual connection or skip connection to residual mappings instead of directly learning the desired underlying mapping. Hence, it addresses the problem of vanishing gradients and enables the more effective training of very deep neural networks. Chili dataset in this study is shown in Fig. 6, consists of 200 images as the small data to be trained by the transfer learning models. Images were captured by Webcam Logitech C920 with 1920×1080 pixels. The distance between the camera and the object was 20 cm. The images were taken in various weather conditions.

Fig. 6. Illustration of chili dataset trained in this study

The images for the dataset illustrated in Figure 6 are collected from the chili grown in our agrivoltaics farm located in Gandus, South Sumatra, Indonesia (3.0073° S, 104.7197° E). The 200 images for small data training are uniformly named and labeled into three classes: *Buah Cabai* 2 (2 chilies), *Buah Cabai* 3 (3 chilies), and *Buah Cabai* 6 (6 chilies), as shown in Table 1. The label was written in Indonesia, where *Buah Cabai* refers to chili. The six chilies class was chosen because there were at most six chilies on a single branch. It is assumed that if the proposed method correctly recognizes six chilies, it will be effective for four and five-chilies prediction/counting. The dataset is randomly partitioned into training, validation, and testing, as shown in Table 1. During data partition, the batch size is also decided to match the training process and expected outcome. Hyperparameter tuning, such as batch size, learning rate, and epoch in this paper, is given in Table 2.

Table 1. Training and testing dataset

Class Name	Count	Training	Testing
Buah cabai 2	**300**	**200**	**100**
Buah cabai 3	**300**	**200**	**100**
Buah cabai 6	**300**	**200**	**100**

Table 2. Hyperparameter tuning

Batch size	Learning Rate	Epoch	Hidden layer	Dropout
16	**0,001**	**100**	**256**	**0.4**

The steps of predicting crop are including import library, load pre-trained model, freeze layers, add custom layers (fine-tuning), compile the model, load and pre-process dataset, and train the model. Validation data is used to monitor the training process and prevent overfitting and evaluate the model to assess its performance. The activation considered in this study is ReLu in the input layers and SoftMax in the output layer. The pseudocode of the model training in this study is given by:

a- **EfficientNetV2L**

```
img_shape = (img_size[0],img_size[1] , 3)
num_class = len(classes)
base_model = tf.keras.applications.
EfficientNetV2L(include_top = False , weights
= 'imagenet'
input_shape = img_shape, pooling= 'max')
model = Sequential([
base_model
BatchNormalization(axis= -1 , momentum=
0.99 , epsilon= 0.001),
Dense(512, kernel_regularizer =
regularizers.l2(l= 0.016) , activity_regularizer
= regularizers.l1(0.006),
bias_regularizer= regularizers.l1(0.006) ,
activation = 'relu'),
Dropout(rate= 0.4 , seed = 75),=
```

b- **EfficientNetV2M**

```
img_shape=(img_size[0],img_size[1],3)
num_class = len(classes)=
base_model = tf.keras.applications.
EfficientNetV2M(include_top = False ,
weights = 'imagenet',
input_shape = img_shape, pooling= 'max')
model = Sequential
base_model
```

BatchNormalization(axis= -1 , momentum= 0.99 , epsilon= 0.001),
Dense(512, kernel_regularizer = regularizers.l2(l= 0.016),activity_regularizer = regularizers.l1(0.006),
bias_regularizer= regularizers.l1(0.006) , activation = 'relu'),
Dropout(rate= 0.4 , seed = 75),
Dense(num_class , activation = 'softmax')

c- **RestNet50**

img_shape=(img_size[0],img_size[1],3)
num_class = len(classes)
base_model = tf.keras.applications.ResNet50(include_top = False , weights = 'imagenet'
input_shape = img_shape, pooling= 'max')
model = Sequential
base_model
BatchNormalization(axis= -1 , momentum= 0.99 , epsilon= 0.001),
Dense(512, kernel_regularizer = regularizers.l2(l= 0.016) , activity_regularizer = regularizers.l1(0.006),
bias_regularizer= regularizers.l1(0.006) , activation = 'relu')
Dropout(rate= 0.4 , seed = 75),
Dense(num_class , activation = 'softmax')

The transfer learning model performance can be assessed by accuracy, precision, Recall, and F1-score. Precision is defined as the ratio of chili images correctly labeled based on three set classes (Buah Cabai 2, Buah Cabai 3, and Buah Cabai 6) to the total number of correctly predicted images identified based on the number of chilies captured in those images. Precision is given as (15):

$$\mathbf{Precision} = \frac{\mathbf{TP}}{\mathbf{TP + FP}}, \qquad (6)$$

where TP is true positive (the number of cases where the model correctly predicts a number of chilies on an image) and FP is false positive (The model incorrectly predicts positive instances). Recall is defined as the ratio of chilies correctly counted and the actual number of chilies in an image. The Recall, also known as Sensitivity of True Positive Rate, is given by (15):

$$\mathbf{Recall} = \frac{\mathbf{TP}}{\mathbf{TP + FN}}. \qquad (7)$$

F1-score is a measure that harmonizes Precision and Recall, which can be written as(15):

$$\mathbf{F1score} = 2\,\frac{\mathbf{Precision} \times \mathbf{Recall}}{\mathbf{Precision} + \mathbf{Recal}}. \qquad (8)$$

Accuracy is the overall performance of the model in predicting the number of chili crops in a given image. Accuracy can be presented as(15):

$$\mathbf{Accuracy} = \frac{\mathbf{TP + TN}}{(\mathbf{TP + TN})(\mathbf{FP + FN})}. \qquad (9)$$

C- **Ecological Impact Assessment**

Life Cycle Analysis (LCA) is a comprehensive method for assessing the environmental impacts associated with all stages of a product's life, from raw material extraction through to end-of-life disposal. In the context of agrivoltaic systems, LCA helps evaluate the sustainability of integrating photovoltaic (PV) solar panels with agricultural practices, focusing on aspects such as energy use, carbon emissions, water use, and overall ecological impact.

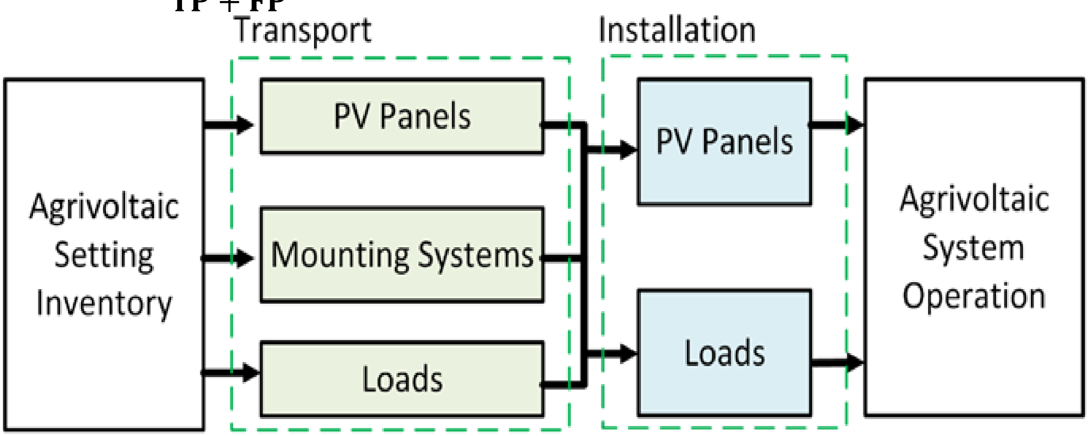


Fig. 7. LCA block diagram of PV system to power the agrivoltaic system

The goal of this LCA is to assess the environmental impacts of an agrivoltaic system compared to traditional agricultural practices. This includes evaluating the energy and material inputs, operational efficiency, and the benefits of renewable energy integration. The LCA analysis in this study, which is illustrated in Figure 7, covers the PV panels installation, agricultural input (seeds, fertilizer, and harvesting), and operational (crop cultivation, energy generation, irrigation, and maintenance) phase. Since the agrivoltaics system is still running and in experimental phase, this study excludes decommissioning, recycling, and waste management.

RESULT AND DISCUSSION

This section presents and interprets the findings from the study on harvest prediction in agrivoltaic chili farming using Convolutional Neural Network (CNN) transfer learning, with a focus on ecological sustainability.

A. Microclimate controlled greenhouse results: The main focus of this study is the automatic climate-controlled greenhouse and how the agrivoltaics system setting considered in this study is shown in Fig. 8 where A is the system outside greenhouse and B is the solar-power greenhouse. Both A and B agrivoltaics system employ automatic irrigation and fertigation system. The main difference between both systems is that the greenhouse has the microclimate system controlled to meet the needs of chili or any plants inside the greenhouse.

Fig. 8. PV system to power the agrivoltaic system

The interface of IoT monitoring of micro-climate of the considered agrivoltaic setting is given in Fig. 9 where the IoT monitoring shows the data given by sensor, watering system, fogging system, and water tank level. The monitoring data is updated online and giving the current situation of micro-climate to give the farmer update information.

Fig. 9. IoT monitoring interface for the agrivoltaic system

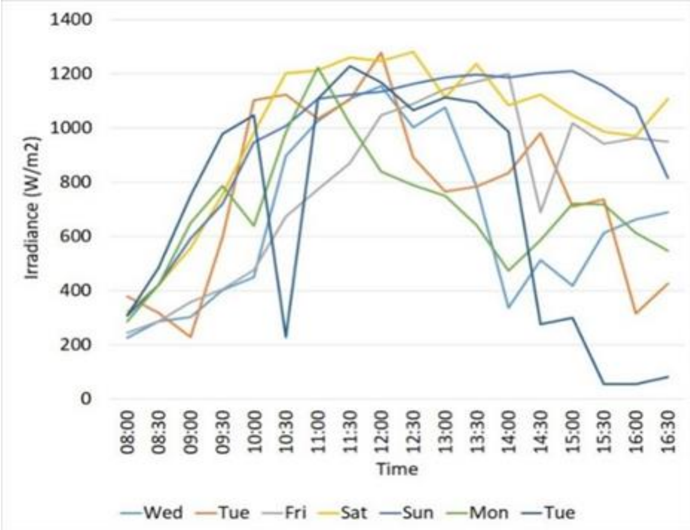


Fig. 10. Irradiance for 1 week experiment

The agrivoltaic system highly dependent on solar irradiance for supply the electronics and the micro-climate condition is highly affected by the weather. The irradiance during 1 week experiment is given in Fig 10. The high irradiance data shows the solar energy potential in Palembang.

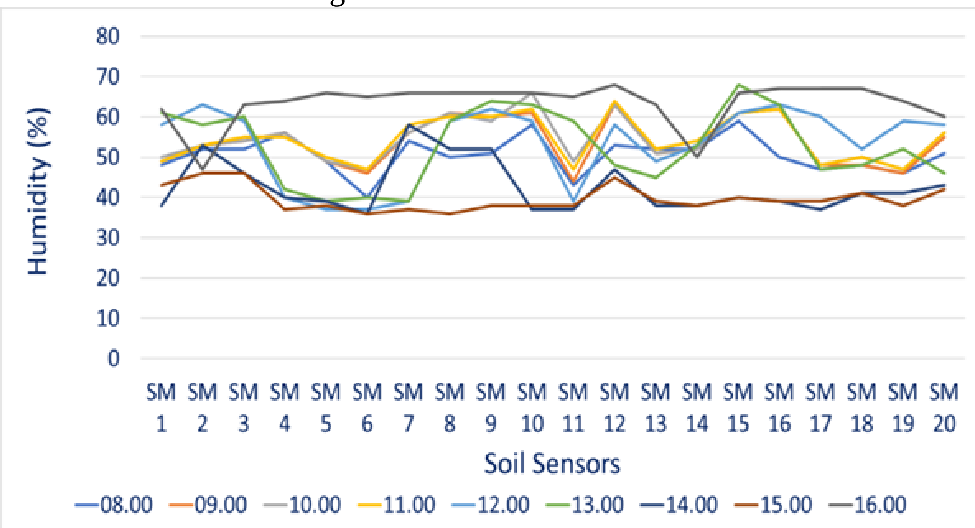


Fig. 11. Humidity data produced by soil humidity sensors inside greenhouse

The irradiance data in Fig. 10 matches with the (1) and (2) where the more irradiance provided, the more electricity generated. The data results satisfy the mathematical modeling given in (3) and (4) showing that micro-climate inside the agrivoltaic setting in this study can be controlled by proposed method in Fig. 1.

System Production			
Useful energy from solar	1621.32 kWh/year	Perf. Ratio PR	71.70 %
Available solar energy	1744.67 kWh/year	Solar Fraction SF	93.01 %
Excess (unused)	62.08 kWh/year		
Loss of Load		**Battery aging (State of Wear)**	
Time Fraction	7.0 %	Cycles SOW	88.5 %
Missing Energy	121.92 kWh/year	Static SOW	80.0 %

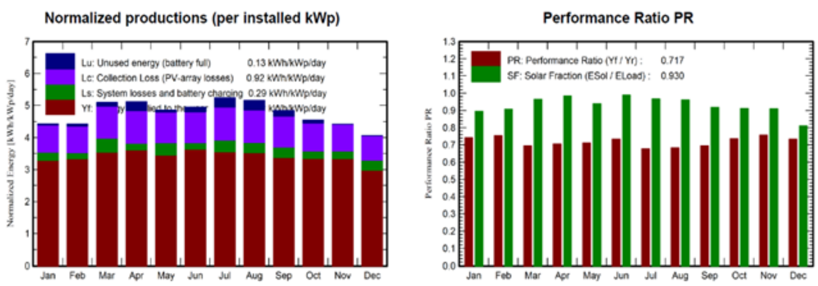


Fig. 12. The illustration of crop counting results

Fig. 12 shows that the possible generated electricity annually is 1744.67 kWH/year which are more than enough to power the agrivoltaics system in this study. This result is simulated with irradiance data available from PVsyst Software.

B. Crop Yield Prediction Results

The chilies plant in this study is growing on our experimental farm located in the Gandus Sub-District in Palembang, Indonesia. The average temperature is 30^{o}C, and tropical weather is ideal for chili growth. Chili is one of the favourite ingredients of Indonesia Cuisine. Chili is a very important ingredient, and there is no Indonesian main dish that can be cooked without chili. The images of chilies are categorized into 3 classes, and 3 transfer learning models are assigned to predict the crops.

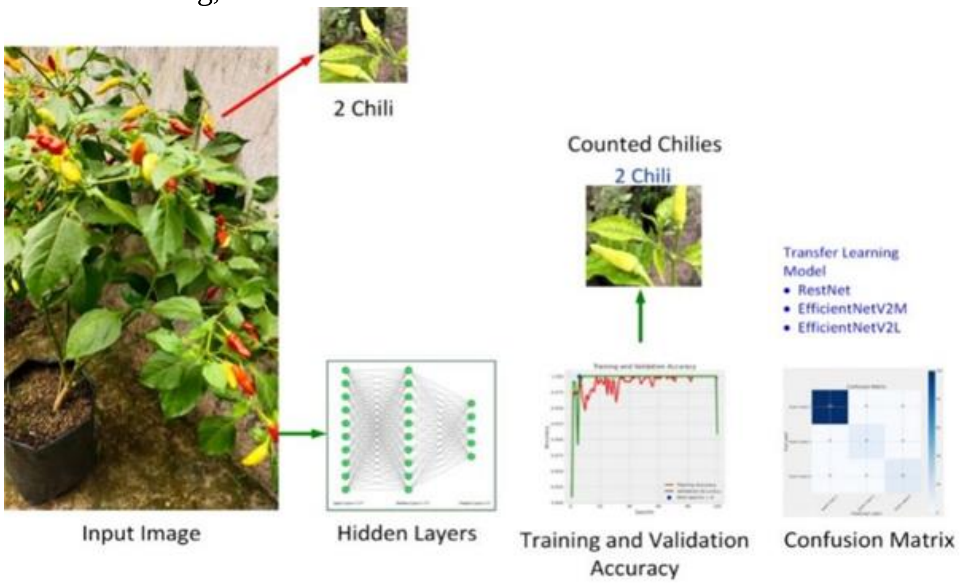
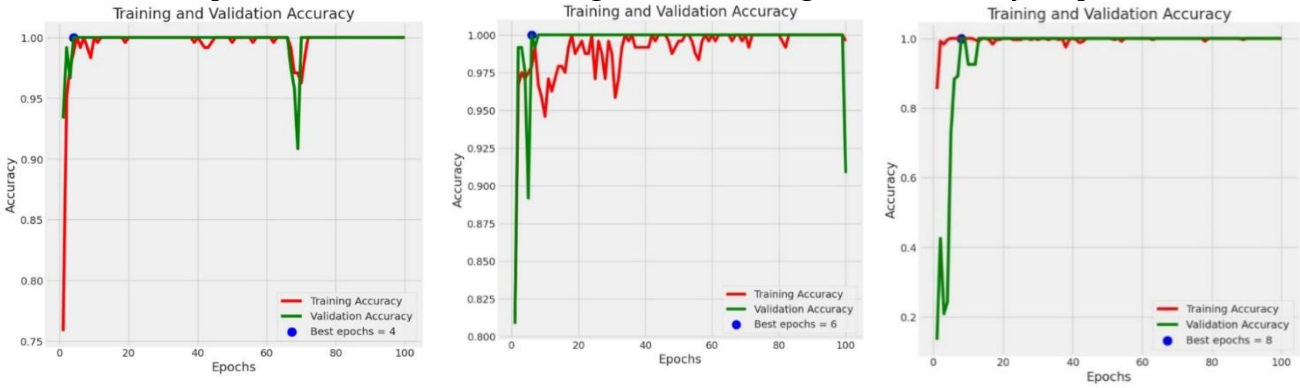


Fig. 13. The illustration of crop counting results

Fig. 13 shows that images for the chili dataset considered in this study were captured from our chilies that are grew in our experimental farm, and the results is the crop counting as shown in Fig. 14 which system performance is given by confusion matrix, training and validation accuracy, training and validation loss, and finally the confusion matrix to show how effective the proposed method is.

Fig. 14. Result of crop counting prediction with 3 transfer learning models

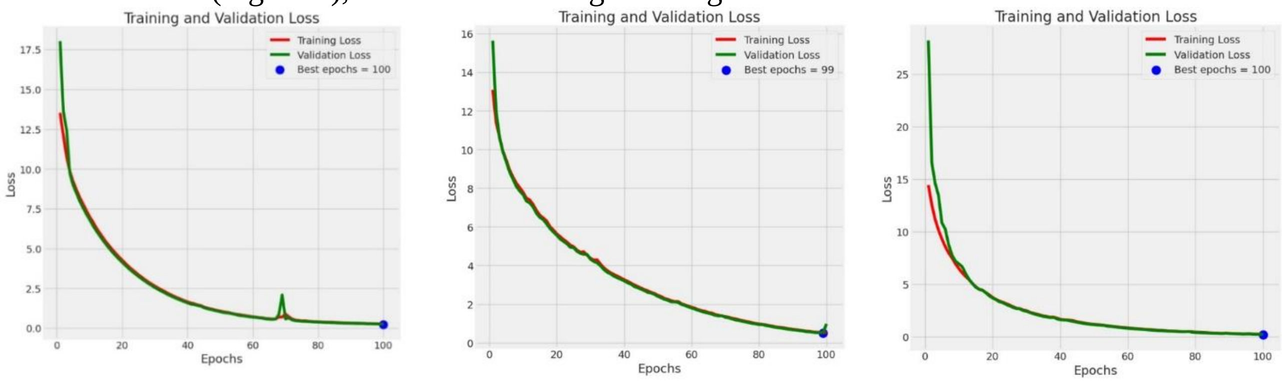
Fig.14 shows the result of crop counting prediction where the proposed method correctly counts the number of chili in an image, where Buah cabai 2 means 2 chilies, buah cabai 3 means 3 chilies, and buah cabai 6 is 6 chilies. Fig. 15 presents the training and validation accuracy, where all the models show convergence between training and validation. Convergence is necessary to determine the point at which the training process reaches a stable state, and parameters such as weights and biases have reached the accurate prediction for the training data. Transfer learning creates faster convergence due to a pre-trained large dataset employed beforehand. The convergence in Fig. 15 also indicates that the training errors have stopped decreasing or have reached a minimum level of acceptable errors. The error, such as overfitting, is overcome by dropout.



(a) EfficientNetV2L **(b)EfficientNetV2M** **(c) RestNet50**

Fig. 15. Training and validation accuracy results of 3 transfer learning models

This study implements 100 epochs for all the models, and the best epoch for EfficientNetV2L is 4 (Fig. 15a), EfficientNetV2M is 6 (Fig. 15b), and RestNet50 is 8 (Fig. 15c), where the training and validation start to convergence. Overall, the performance, convergence, and generalization capability in the proposed method are proven effective by the results in Fig. 16.



(a) EfficientNetV2L **(b)EfficientNetV2M** **(c) RestNet50**

Fig. 16. Training and validation lost results of 3 transfer learning models

Fig. 16 indicates the training and validation loss results of three transfer learning models. The best epoch for EfficientNetV2L is 100% (Fig. 16a), EfficientNetV2M is 99% (Fig. 16b), and RestNet50 is 100% (Fig. 16c). The training and validation loss is zero, indicating that the model is learning effectively, which is proven by correct prediction in Fig. 16 and total performance analysis in Table 3. The total model performance evaluation is listed in Table 3, which shows that EfficentNetV2L and RestNet have an accuracy of 100%. EfficientNetV2M has lower accuracy due to the low dataset performance. During counting three chilies, EfficientNetV2M returns a result of zero because the three chilies are stacked together, and their hue is green, which is very similar to the leaves as shown in Fig 17, and this is also indicated by the underfitting in training and validation accuracy (Fig 15b). The tuning includes a drop of 0.4, and the seed is 75.

Table 3. Model performance evaluation

Classes	Model	Precision	Recall	F1-Score	Accuracy
	EfficientNetV2L	1	1	1	1
Buah Cabai 2	EfficientNetV2M	0.92	1	0.96	0.93
	RestNet50	1	1	1	1
	EfficientNetV2L	1	1	1	1
Buah Cabai 3	EfficientNetV2M	0	0	0	0.93
	RestNet50	1	1	1	1
	EfficientNetV2L	1	1	1	1
Buah Cabai 6	EfficientNetV2M	1	1	1	0.93
	RestNet50	1	1	1	1

Fig. 17. chilies image

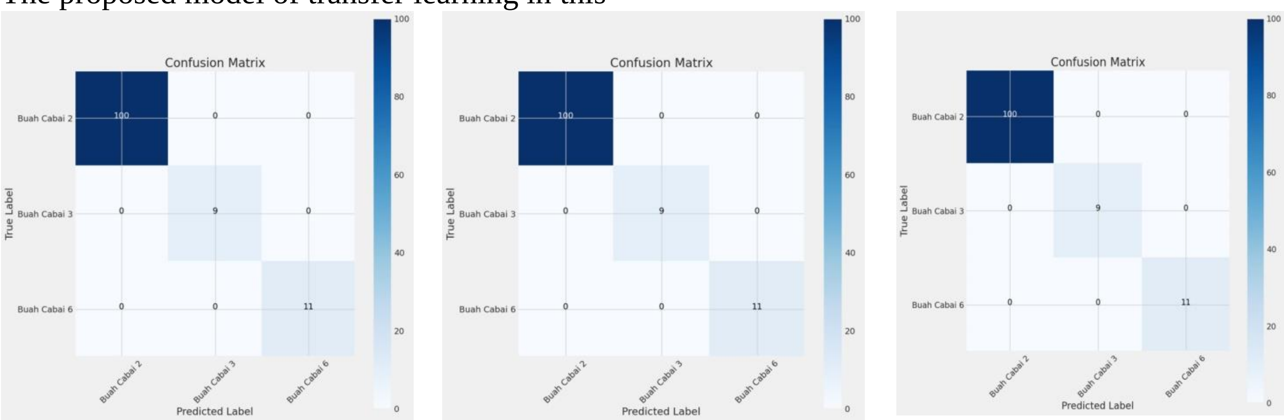
Fig. 18. Confusion matrix results of 3 transfer learning models

Note: Buah cabai 1 : 1 chili, Buah Cabai 2: 2 chilies, and Buah Cabai 6 are 6 chilies

Fig. 18 shows the confusion matrix of three proposed models where the diagonal indicates the number of correctly classified and the off-diagonal shows the misclassification. The confusion matrix is related to Table 1 of the model performance list. The overall performance or accuracy is 100%; hence, all the true labels and predictions are the same. The F1 score, which combines Precision and Recall, shows that it is 96% for EfficientNetV2M, and other models are 100%. The proposed model of transfer learning in this study has proven effective in predicting crop counting for chili harvest prediction.

D- Life Cycle Analysis Simulation

The LCA to demonstrate the environmental impact of agrivoltaics system considered in this study. The main environmental impact is during the process of controlling micro-climate inside the solar-powered greenhouse; however, the agrivoltaics system plays important roles in ensuring the efficient usage of water and other resources tailored to plants' need.



(a) EfficientNetV2L **(b)EfficientNetV2M** **(c) RestNet50**

Fig. 18. LCA of agrivoltaics system in this study

Note: Buah cabai 1 : 1 chili, Buah Cabai 2: 2 chilies, and Buah Cabai 6 are 6 chilies.

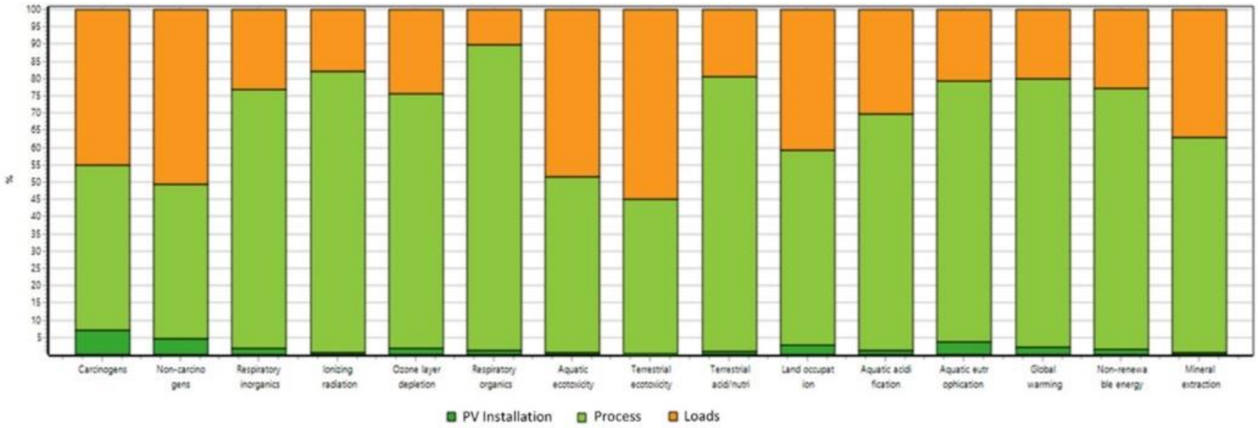


Fig. 18. LCA of agrivoltaics system in this study.

The integration of solar panels and optimized resource use led to a 40% reduction in the carbon footprint of the farming operation. The reduced need for external energy sources and lower resource wastage contributed significantly to this reduction. The optimized use of fertilizers and water improved soil health over time, as evidenced by lower soil erosion rates and improved soil nutrient profiles. This aligns with the goals of sustainable agriculture, promoting long-term ecological balance. The reduction in chemical inputs and optimized farming practices supported local biodiversity. The use of integrated pest management practices, guided by accurate predictions, reduced the need for chemical pesticides, benefiting beneficial insects and local flora.

CONCLUSION

The integration of advanced technologies in agriculture offers promising avenues for enhancing sustainability and productivity. This study investigates the ecological impacts and benefits of using Convolutional Neural Network (CNN) transfer learning for harvest prediction in an agrivoltaic chili farming system. The micro-climate inside the experimental solar-powered greenhouse is automatically controlled and monitored by IoT to ensure ideal condition for the plant. The installed PV panels are beneficial in the place where the electricity from utility is intermittent. The experimental and simulation results of agrivoltaics analysis shows that the system is working as expected. Crop yield prediction is crucial to ensure the efficient harvest management, and this study presents 3 transfer learning models for chili crop counting to predict chili harvest yield. The models are EfficientNet V2L, EfficientNetV2M, and RestNet 50, which were chosen due to the high accuracy of the pre-trained model list in the Keras Application. The experimental results show that the proposed method correctly counts the chili crops in an image where the accuracy of EfficientNetV2L is 100%, EfficientNetV2M is 93%, and RestNet 50 is 100%. The results also show quick convergence in training and validation accuracy, which indicates that the model learning effectively. Therefore, this study shows that transfer learning is ideal for crop counting to effectively predict how much resources need to be prepared during harvesting and harvest handling.

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