



Implementation of VGG19 Model for Pest Detection on Mustard Leaves

Raden Ronggo Bintang Pratomo Prawirodirjo^{1*}, Hirzan Fakhruy Syakirin², Febriansyah³, Zahra Windi Aulia⁴, Putri Sahira⁵, Budi Prayitno⁶, Riki Ruli Affandi Siregar⁷

^{1,2,3} Informatics Engineering, Institut Teknologi PLN, Indonesia

⁴ System Information, Institut Teknologi PLN, Indonesia

⁵ Electrical Engineering, Institut Teknologi PLN, Indonesia

^{1*}raden2131005@itpln.ac.id, ²hirzan2131014@itpln.ac.id, ³febriansyah2231049@itpln.ac.id, ⁴zahra2332013@itpln.ac.id, ⁵putri2311009@itpln.ac.id, ⁶budiprayitno@itpln.ac.id, ⁷riki.ruli@itpln.ac.id

Abstract: Green mustard is a leading agricultural commodity in Indonesia but often faces pest attacks such as *Spodoptera litura*, which can reduce productivity by up to 85%. This study aims to develop an automated pesticide sprayer prototype using Convolutional Neural Network (CNN) technology with the VGG19 architecture. The system utilizes Raspberry Pi, Arduino, ESP8266, and a camera to detect pests in real-time and accurately spray pesticides. The dataset used consists of 1,380 images, divided into 10% for testing, 25% for validation, and 75% for training. The model evaluation values for the 'mustard with pests' class achieved precision, recall, and F1-Score of 96% each, while for the 'mustard without pests' class they were 95% each. In addition, the MAPE (Mean Absolute Percentage Error) value of 4.61% shows that the percentage error of the model prediction is very small. The developed VGG19 model achieved an accuracy of 95% and high efficiency after conversion to the TFLite format, reducing model size by 75.57%. This tool is highly recommended to enhance farmers' work efficiency, reduce excessive pesticide use, and support sustainable agriculture. Its ability to operate autonomously and precisely makes it an ideal solution to assist farmers regarding pest problems.

Keywords: Green mustard, *Spodoptera litura*, Convolutional Neural Network (CNN), VGG19, automated pesticide sprayer.

1. INTRODUCTION

One of the leading commodities in the agricultural sector is mustard, especially green mustard, which has high economic value and is one of Indonesia's main export commodities [1]. The main problem for mustard farmers is the attack of plant damaging organisms (OPTs) that can lead to a reduction in the quality and quantity of mustard plants. If the pests are not controlled, they can cause severe damage to the plants and reduce productivity. For farmers, this certainly means a loss of both quality and quantity [2]. Identification of plants affected by pests requires special attention to the symptoms or signs shown by the plant, especially on the leaves. One of the pests that attack mustard plants is armyworms [3]. Symptoms of attack caused by the larval stadia of armyworms that are still small damage the leaves by leaving the remains of the epidermis at the top and only the bones of the leaves. Large larvae eat the leaf bones and fruit [4]. This pest attack causes yield losses of up to 85%, and can even cause crop failure [5]. Therefore, early detection of symptoms of pest infestation is important to avoid further losses. Timely detection of pests and accurate use of pesticides are the biggest challenges in agriculture.

Currently, farmers still use pesticide spraying on pests manually and still rely on human labor. This method is less effective, not environmentally friendly, and poses health risks due to direct pesticide exposure [6]. The farmers are constantly dealing with pesticides directly which makes the health of the





farmers less secure [7]. Direct exposure to anti-pest substances (pesticides) often causes long-term health effects. In addition, the use of pesticides by farmers is no longer based on indicative needs, but many farmers use pesticides excessively by spraying continuously, without paying attention to wind direction and without paying attention to the presence or absence of pests [8]. This method is not fully optimal and requires further development to reduce dependence on human labor and minimize environmental impacts. Therefore, technological innovations in anti-pest spraying are needed to increase efficiency, reduce environmental impacts, and minimize farmers' health risks.

Along with the development of technology, artificial intelligence-based image processing, such as Convolutional Neural Networks (CNN), has been widely used in plant disease detection. Image processing involves processing images to get information or images as output. Machine learning is one part of artificial intelligence that works by processing image data to identify patterns. Deep learning is one of the methods of applying machine learning which includes Convolutional Neural Network (CNN) in image data classification [9]. CNN is a type of neural network that is effective in managing image data and has been widely used in various studies in agriculture. Deep learning, especially CNN, has become an interesting topic in the development of complex data models. CNN has proven to be effective in image classification, including pest detection. One of the available CNN architectures is VGG19 [10]. Previous research shows that CNN architectures such as VGG19 have high accuracy performance in detecting pests, and achieve excellent accuracy [11][12]. VGG19 is a CNN network architecture which is one version of the VGG architecture, has a layer depth of 19, consisting of 16 Convolutional Layer, 5 Max Pooling Layer, 3 Fully-Connected Layer, and 1 SoftMax Layer [13]. In this research, VGG19 is used to detect pests on mustard greens and integrated into a prototype of an automatic pest sprayer.

In the research conducted [14], insect pest classification was carried out using the CNN method with 1363 image images and 13 insect pest classes. The tested model is the result of the training process using a batch size of 16 and epoch 50. The results show that the model managed to achieve a training accuracy rate of 93.81% and a validation accuracy of 81.75%. Meanwhile, at the testing stage, this model managed to achieve an accuracy rate of 80%. The model that has been made successfully predicts correctly as much as 109 testing data out of a total of 136 testing data. Another study [15], using the CNN deep learning method for the identification of disease images on potato leaves. The results obtained show that the highest accuracy value of training data reaches 93% and the highest accuracy of validation data reaches 99%. The next research [16] used the Deep Learning CNN method for the identification of diseased rice leaf images. The highest value of training data accuracy reached a value of 85%, for testing data 86%, and for validation data reached a value of 95%. A different study [17] used deep learning methods and Convolutional Neural Network (CNN) algorithms to identify diseases in tomato plants through leaves with Android-based applications. This model showed 94% accuracy when tested with images from the gallery and 80% when using images taken directly from the camera. Another study [18] used CNN with VGG-19 model architecture to classify the ripeness level of Cavendish banana fruit. This study used 9,000 datasets with 80% used as training data, 10% as validation data, and 10% as test data. The classification results using the VGG-19 model showed an accuracy of 97% at epochs 32, 64, and 96.

Based on this, the author presents a solution to overcome the existing problems, namely by making an automation tool for spraying anti-pests. In this research, the author will create a prototype of an automation tool for spraying anti-pests. This research continues a previous study that compares the performance of CNN architectures in pest detection and integrates the best results into an automation system. The architectures compared in that study include VGG19, InceptionV3, and Xception. The results obtained show that VGG19 has very good accuracy in detecting pests so that the automation tool made will integrate CNN with VGG19 architecture. With the application of this technology, it is expected that the tool can help farmers improve work efficiency, reduce the use of excessive pesticides, and create a more sustainable agricultural ecosystem. This tool is also expected to be able to increase the production of mustard greens in Indonesia, especially in Pagaralam City, in order to meet the export needs of mustard greens commodities.



This prototype uses Raspberry Pi, Arduino, esp8266, and camera. In its implementation, Raspberry Pi as a mini computer to run the CNN model, while Arduino is used to control the pump and movement of the device. In addition, the device is equipped with an ESP8266 for data communication and a camera for image acquisition. The system is designed to automatically spray anti-pests based on pest detection results from the CNN model, making it more efficient, environmentally friendly, and reducing health risks for farmers. The data used in this study is a combination of data from previous researchers and data taken independently. Ten percent of the total 1,380 data will be taken for test data and randomly selected. Furthermore, the remaining 1241 image data, 25% will be used for validation data and 75% for training data.

The author hopes that this tool can help in terms of human labor and can reduce pollution from exhaust gases from engine use, so to speak, this machine will use electric power. Not only to simplify and speed up the work, this tool is also expected to reduce health risks for farmers. In addition, in the future it is hoped that this can help farmers get information from the tool to be a big step towards more efficient inputs for pest control systems to reduce the use of chemical pesticides and a more sustainable agricultural ecosystem. This is expected to increase the amount of green mustard production in Indonesia, especially in Pagaralam City by maximizing the agricultural process in meeting the export needs of green mustard commodities in Indonesia.

2. RESEARCH METHODOLOGY

The outline of the research method used in this study consists of several workflow steps which are explained in Figure 1.

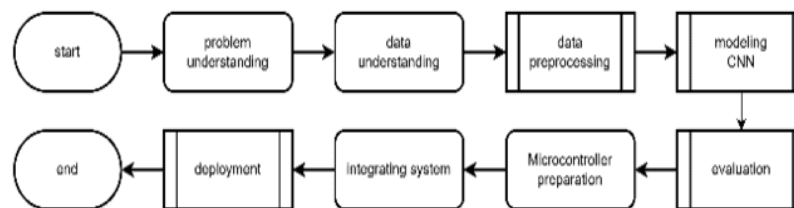


Figure 1. Research workflow

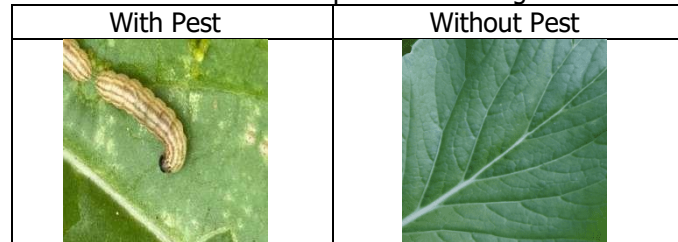
2.1. Problem Understanding

At this stage, an analysis is conducted on the image classification process and the relevance of the problems faced. This research focuses on developing a classification system that aims not only to identify plant conditions but also to facilitate automatic actions, such as pesticide spraying. The expected outcomes of this classification process include more effective fertilization, reduced pest attacks on crops, and more efficient pest management through an automated pesticide spraying system that can operate autonomously. The process consists of goal setting, situation analysis, determining the objectives of image classification, and strategic planning. Ultimately, the final objective is to create a tool capable of automatically spraying pesticides based on the detected condition of the plants. The background and objectives of the research have been outlined prior to detailing this phase.

2.2. Data Understanding

At this stage, an in-depth analysis is necessary to understand the characteristics of the data and identify potential data quality issues. The data used in this research is a combination of data previously collected independently by the researchers and newly gathered data. The Jirifarm mustard green plantation (Jl. Alun Alun No.I No.58, Curug Kulon, Kec. Curug, Kabupaten Tangerang, Banten 15810) serves as the source of the newly collected data, while the data from previous researchers was obtained from Kaggle via the following link: <https://www.kaggle.com/datasets/cendekialuthfietanz/caisim>. The following table of sample from the dataset.

Table 1. Sample of mustard green leaf



2.3. Data Preprocessing

The labor-intensive phase is a term often used to describe this stage. Data collection, data enhancement, and data splitting are some of the actions undertaken. Figure 2 illustrates the workflow of this data preprocessing process.

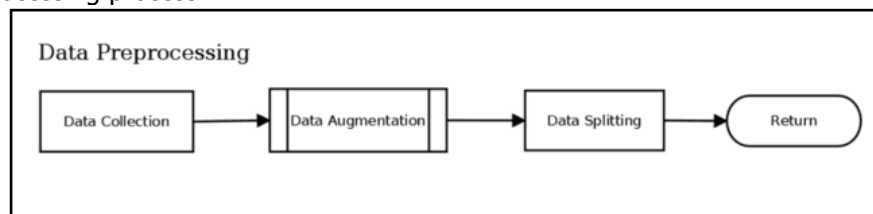


Figure 2. Data Preprocessing Flow

In the data collection step, 999 images from previous researchers were combined with 251 manually added images, along with 150 images collected by the authors at the research site. Subsequently, for each architecture, rescaling and the preprocess_input function were used to perform data augmentation within the program code. After data enhancement, the next step was data splitting. Ten percent of the total 1,380 data points were randomly selected as test data. Following the separation of test and training data, program code was accordingly adjusted. From the remaining 1,241 images, 25% were allocated for validation data, while 75% were designated for training data.

Table 2. Data preparation

Parameter	Data Train	Data Validation	Data Testing
Target size	256 x 256	256 x 256	256 x 256
Color mode	rgb	rgb	rgb
Subset	training	validation	-
Batch	32	32	32
Proportion	67.5%	22.5%	10%

2.4. Modelling CNN

To determine the appropriate deep learning technique, several steps were undertaken, including selecting tools, methods, and algorithms, as well as optimizing hyperparameters to achieve the best possible accuracy. Classification was employed in deep learning, specifically utilizing the Convolutional Neural Network (CNN) algorithm. For this research, the CNN model architecture integrated with the VGG19 model was employed. This model was chosen for its ability to process hierarchical image features and its proven effectiveness in various image classification applications.

2.5. Model Evaluation

The model evaluation was conducted thoroughly to ensure that the developed model aligns with the initial objectives. The evaluation results for this study utilized the Confusion Matrix to calculate precision, recall, and F1 score. Additionally, the Mean Absolute Percentage Error (MAPE) was included as an assessment method to measure the degree of error or loss in the model's prediction of pests on mustard leaves. Furthermore, the system's performance in terms of computational resource usage was also evaluated. This evaluation included CPU usage to measure processing capacity, RAM usage to assess memory consumption, GPU usage and GPU memory to analyze the usage of the graphics processing unit, and processing time to calculate the duration of model training and inference. These results will later serve as a benchmark for assessing the effectiveness of a model in terms of both accuracy and computational efficiency. The outcomes will also be used to evaluate the model's feasibility for real-world deployment, considering accuracy, resource requirements, and processing speed.

2.6. Microcontroller Preparation

This stage involves the preparation of microcontroller requirements, including Arduino, ESP8266, a camera, and a mini computer. The researchers assembled these components into a single system connected to the main board. The concept utilizes a Raspberry Pi as the mini computer, while the Arduino is tasked with controlling the water pump and the movement of the device. The integration of these components ensures seamless connectivity and operational functionality in the system.

2.7. Integrating System

This stage involves the integration of the Raspberry Pi mini computer with the Arduino microcontroller via a USB connection. The choice of USB as the communication medium is based on its advantages over other methods, such as pin interfaces, as it offers stable data transfer speeds, minimal interference, and low latency. The Raspberry Pi acts as the primary processing hub running the artificial intelligence model, while the Arduino functions as an execution device managing hardware components such as actuators and sensors. Processed data from the AI model on the Raspberry Pi is transmitted to the Arduino using a serial communication protocol over USB, enabling the execution of programmed functions, such as pesticide spraying. This approach also simplifies system debugging and development, as USB communication facilitates real-time data monitoring with a compatible interface, ensuring smoother system performance and easier troubleshooting.

2.8. Deployment

The deployment stage is a crucial phase in this research, where the developed model is implemented to produce outputs processed by the microcontroller. The process begins with running the model on the mini computer, followed by transmitting the output to the microcontroller. The microcontroller will process this output and determine whether pests are detected. If pests are detected, the system will automatically activate the pesticide spraying mechanism. If no pests are detected, the system will return to its initial mode. The workflow of the deployment stage is illustrated in Figure 3.

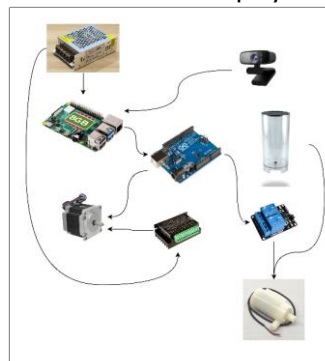


Figure 3. Device concept design

As shown in Figure 3, the Raspberry Pi 4B serves as the main computer for processing the CNN model and receiving input from the camera. The Raspberry Pi 4B is powered by a power supply and sends signals to the Arduino device. The Arduino device acts as the microcontroller for this project, processing the signals from the Raspberry Pi. When the Raspberry Pi detects a pest, the Arduino takes control of the connected devices. It sends a signal to the relay module to activate the pesticide sprayer and manages the stepper motor to slow its speed. The stepper motor also receives power directly from the power supply.

3. RESULT AND DISCUSSIONS

3.1. VGG19 Model

VGG19 adalah sebuah arsitektur jaringan CNN yang merupakan salah satu versi dari arsitektur VGG, memiliki kedalaman layer sebanyak 19, terdiri dari 16 *Convolutional Layer*, 5 *Max Pooling Layer*, 3 *Fully-Connected Layer*, dan 1 *SoftMax Layer* [1]. Parameter yang diberikan pada model VGG19 ini antara lain.

Table 4. VGG19 transfer learning architecture

Model	Sequential	
Layer	Output shape	Total Params
VGG19	8, 8, 512	20.024.384
Flatten	32768	0
Dense 0	1024	33555456
Dense 1	2	2050

Figure 4 will show result of the testing using the VGG19 model

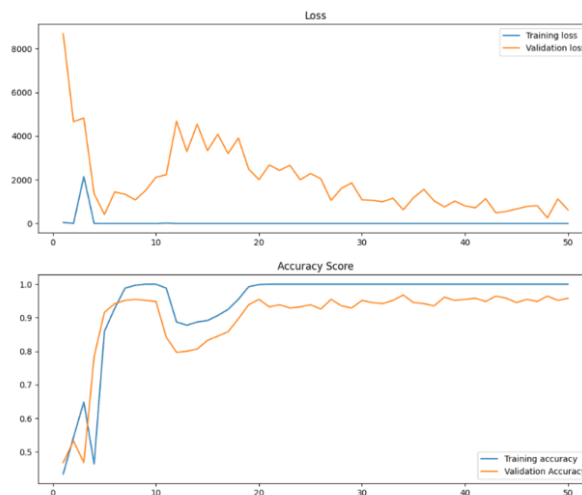


Figure 4. VGG19 training result graph

In Figure 4 the graph shows the results of training a model with the VGG19 architecture for pest recognition on mustard greens. The loss graph shows that the model is learning well. Although the model accuracy decreased in the 10th to 20th epochs, the accuracy was maintained until the end of training.

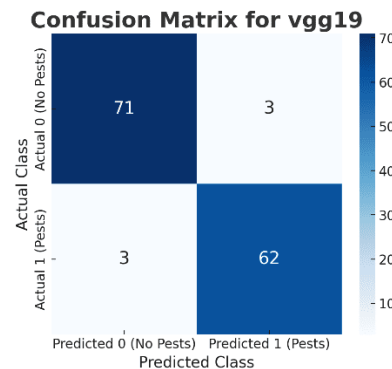


Figure 5. Confusion Matrix for VGG19

The results of the confusion matrix presented in Table 5 can be explained as follows: There are 71 data points of mustard greens with pests correctly predicted as their own class, 3 data points of mustard greens with pests incorrectly predicted as the class of mustard greens without pests, 3 data points of mustard greens without pests incorrectly predicted as mustard greens with pests, and 62 data points of mustard greens without pests correctly predicted as their own class. Based on these results, the total data predicted as mustard greens with pests is 74, while the total data predicted as mustard greens without pests is 65. For Class 0 (mustard greens with pests), the precision, recall, and F1-score are each 0.96. For Class 1 (mustard greens without pests), the precision, recall, and F1-score are each 0.95. Additionally, the Mean Absolute Percentage Error (MAPE) for the model is 4.61. The MAPE result obtained from the model training is approximately 4.61. With a score below 10%, it can be concluded that the model's percentage of error falls within the "very good" criteria. The MAPE result obtained from the model training is approximately 4.61. With a score below 10%, it can be concluded that the model's percentage of error falls within the "very good" criteria.

3.2. Model Conversion

The VGG19 model developed was converted from H5 format to TFLite to optimize size and efficiency for mobile devices. The conversion resulted in a 75.57% reduction in model size, from 78.6 MB to 18.3 MB. This optimization was achieved through techniques such as 8-bit integer quantization, removal of unnecessary operations, and graph model optimization.

Table 6. Performance comparison table

Metrics	H5 Model	TFLite Model
Accuracy	95.5%	94.8%
Inference Time	850ms	320ms
RAM Usage	245MB	62MB

The testing results indicated a minimal accuracy drop of 0.7%, accompanied by a significant improvement in inference time efficiency of 62.35% and a 72.24% reduction in RAM usage. Validation using the test dataset demonstrated that the TFLite model's performance remains comparable to the H5 model while offering advantages in size and computational efficiency. This TFLite model is ready for deployment in mobile applications for mustard leaf pest detection, enabling more responsive operations on devices with limited resources.

3.3. Implementation

The study adopted the VGG19 CNN architecture to identify pest infestations on mustard leaves. VGG19 consists of 19 layers, including 16 convolutional layers, 5 max-pooling layers, and 3 fully connected layers. The main parameters of the model include an input image size of 256x256x3 pixels, pretrained weights from ImageNet, and the exclusion of the top fully connected layers. To enhance the learning process, transfer learning techniques were employed. The training results indicated a dip in

Raden Ronggo Bintang Pratomo Prawirodirjo: *Corresponding Author



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accuracy between epochs 10 and 20, but the model's performance stabilized toward the end of the training session.

The evaluation showed highly satisfactory results. Based on the confusion matrix, the model achieved precision, recall, and F1-scores of 0.96 for the "mustard leaves with pests" category and 0.95 for the "mustard leaves without pests" category. Additionally, the low Mean Absolute Percentage Error (MAPE) of 4.61% indicated a very small error margin, classifying the model's performance as "very good."

After training, the model was converted from the H5 format to TFLite to facilitate deployment on mobile devices with resource constraints. The conversion reduced the model size by 75.57%, from 78.6 MB to 18.3 MB. Despite a slight accuracy drop of 0.7%, the TFLite model demonstrated excellent performance with faster inference time (62.35% improvement) and more efficient RAM usage (72.24% reduction). The TFLite model was implemented on a Raspberry Pi 4B, which offers adequate computational support for efficient operations. The implementation involved installing the operating system, configuring libraries such as TensorFlow and OpenCV, and integrating hardware components like Arduino for automated control. This approach successfully created an effective, responsive, and reliable pest detection platform, even on devices with limited resources.

4. CONCLUSION

Based on the research results regarding the implementation of Convolutional Neural Network (CNN) using the VGG19 architecture for pest detection on green mustard leaves, several key points can be concluded. First, the VGG19 model demonstrated excellent performance in recognizing pests on mustard leaves, achieving an accuracy rate of 95% and a Mean Absolute Percentage Error (MAPE) of only 4.61%, categorizing it as "Very Good." The high accuracy indicates that the model effectively classifies images, while the low MAPE reflects minimal prediction errors, making VGG19 an ideal choice for image classification applications, particularly in agriculture, where high precision is essential for pest detection.

Second, the conversion of the VGG19 model from H5 format to TensorFlow Lite (TFLite) proved to offer significant advantages, notably enhanced system efficiency. During the conversion, the model's accuracy only slightly decreased by 0.7%, which is within acceptable limits and does not significantly impact reliability. Moreover, the conversion reduced inference time by 62.35%, allowing the system to process images more quickly, accompanied by a 72.24% reduction in RAM usage. These improvements make the model more efficient and suitable for deployment on low-specification devices like the Raspberry Pi.

Third, in implementation, the Raspberry Pi serves as the image processor for analyzing green mustard leaf images captured by the camera using the deep learning model to detect pests. The analysis results are then sent to Arduino via USB connection. The Arduino plays a vital role in managing the automatic pesticide spraying system based on the predictions made by the VGG19 model. This approach provides a more efficient and automated pest control solution, reducing human intervention and enhancing farmers' productivity.

Lastly, when running the TFLite model on the Raspberry Pi, inference times ranged between 200 ms and 300 ms. This performance is highly commendable for a resource-constrained device, ensuring the system functions in real-time for pest detection and control. This capability enables smooth pest identification processes, offering a practical and effective solution for field applications.

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Raden Ronggo Bintang Pratomo Prawirodirjo: *Corresponding Author



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Prayitno, Riki Ruli Affandi Siregar.



We hope that the results of this research contribute to the advancement of science and technology, particularly in the field of sustainable agriculture. We aspire for this innovation to become a tangible solution in supporting farmers' productivity and reducing the negative impacts on the environment. The developed tool is expected to enhance farmers' efficiency in terms of time and labor while minimizing health risks from direct exposure to pesticides. Moreover, we are optimistic that this technology-based approach can serve as a stepping stone toward more modern and environmentally friendly agricultural practices.

Through this contribution, we aim to make a positive impact not only on farmers but also on the sustainability of the agricultural ecosystem as a whole. We are open to further feedback and collaborations to advance this research in the future.

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Raden Ronggo Bintang Pratomo Prawirodirjo: *Corresponding Author



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