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Convolutional neural network based mobile application for poisonous mushroom detection

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ABSTRACT

Mushroom identification and classification are critical areas of research due to the significant health risks posed by poisonous varieties. Poisonous mushrooms present a considerable threat to public safety as they can be easily mistaken for edible varieties, potentially leading to severe poisoning or even death. The lack of accessible and reliable resources for accurately distinguishing between edible and poisonous mushroom species could result in a growing number of fatalities and health complications within the population. Furthermore, the process of mushroom classification itself is inherently time-consuming, demanding a substantial investment of resources and a comprehensive understanding of mycology. To address these issues, this study aims to develop a mushroom detection prototype specifically for identifying poisonous mushrooms using a mobile application. The application leverages a Convolutional Neural Network (CNN) algorithm to accurately classify mushrooms based on user-submitted images. CNN is one of the deep learning algorithms that is well known for its good performance in image recognition and classification. There are 3 main phases of the research methodology, which cover the data collection and preprocessing, model design and implementation, and performance evaluation. In this study, the developed model achieved a good accuracy of 89%, indicating acceptable performance in distinguishing between edible and poisonous mushrooms. This good accuracy underscores the model's reliability and effectiveness in real-world applications, making it a valuable tool for ensuring public safety.

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1. INTRODUCTION

In recent years, the resurgence of interest in foraging for wild foods, particularly mushrooms, has gained momentum as a part of a broader movement toward sustainable and eco-conscious living. A growing number of individuals, from avid hikers to culinary enthusiasts, are venturing into forests and natural landscapes in search of edible treasures. However, this renewed enthusiasm for mushroom foraging has introduced a critical challenge. Novice foragers and community, driven by a desire to engage with their surroundings and adopt more sustainable dietary practices, often lack the necessary expertise to differentiate between safe, edible mushrooms and their potentially toxic counterparts [1]. This knowledge gap has led to a rise in mushroom-related poisoning incidents, posing a significant concern for public health and safety [2]. Today, it is estimated that there are 1,500,000 species of mushrooms in existence [3].

Food poisoning is a common occurrence among people who are unaware of the negative effects of mushrooms. Even in other countries, cases of poisoning from toxic mushrooms have been reported. However, distinguishing between harmful and edible mushrooms can be challenging due to their abundance and comparison-based characteristics. Accurate classification facilitates the identification of the variety of mushrooms by identifying key characteristics across multiple data sets. Furthermore, the increasing pressure on natural ecosystems caused by unsustainable foraging practices has raised environmental concerns, highlighting the urgent need for accessible and reliable tools that can assist foragers or the community in making informed decisions about the mushrooms they encounter in the wild.

The current landscape of mushroom detection is characterized by a significant lack of improved detection methods [4-5]. Traditional approaches, which frequently rely on manual identification by specialists, are limited in both scalability and applicability in a real-time context [6]. With the growing demand for accurate and efficient mushroom identification, the limited adoption of automated detection methods remains a significant barrier. The absence of robust and accessible solutions, such as computer vision and machine learning systems, causes delays in the rapid and precise detection of mushroom species [7].

This technological gap in detection not only impedes the rapid classification of edible and deadly species but also highlights the critical need for the development and implementation of innovative, technology-driven solutions to overcome the deficiencies in current mushroom detection practices. As a result, there is an urgent need to streamline and simplify the mushroom classification process, making it more accessible and user-friendly for individuals across diverse backgrounds and levels of expertise, thereby fostering a safer and more informed approach to mushroom identification and consumption.

In response to these pressing issues, this study seeks to examine the development and implementation of a mobile application specifically designed to aid foragers in the accurate identification of various mushroom species, while prioritizing user safety and environmental sustainability. The main objective of the study is to classify the poisonous and edible mushrooms using a Convolutional Neural Network (CNN) algorithm on a mobile platform. CNN is highly effective for image classification tasks due to its ability to learn spatial hierarchies of features directly from the image data. It excels at capturing intricate patterns and structures within images, making it well-suited for accurately differentiating between various mushroom species based on their visual characteristics [8].

By providing users with real-time guidance and comprehensive information on mushroom taxonomy and safety, this application endeavors to empower individuals to make responsible and informed choices when foraging for mushrooms, fostering a harmonious coexistence between human activity and the natural world.

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2. LITERATURE REVIEW

2.1 Similar work

Similar works provide examples of previous studies that have implemented deep learning algorithms, especially CNN models, in mushroom classification problems. A study in Iraq has proposed a One-Dimensional Convolutional Neural Network (1D-CNN) to improve the classification of mushrooms [9]. This is due to the difficulty in identifying mushrooms, which have a complex pattern in their features of cap shape, color, and gill structure. The performance has been recorded to achieve high accuracy and reliability. The similar physical appearances of mushrooms have also become a problem in research in India [10]. In that study, the DenseNet-121 structure has been enhanced to increase the accuracy in classifying edible and toxic mushrooms. In Malaysia, a study on mushroom identification was done due to the rise of mushroom poisoning cases [11]. Motivated by a lack of knowledge on local fungi, this study compares Vision Transformers (ViTs) and ResNet models to distinguish between mushroom species in Malaysia. The result shows that the highest accuracy was 90.47% generated by the ViT-L/16 model. Deep learning models have also been compared to detect toxic mushrooms in Karnataka [12]. The study has analyzed the performance of Resnet50, YOLOv5, and AlexNet, which have been successful in classifying the toxic mushrooms with good accuracy. Distinguishing poisonous mushrooms in their natural habitat has always been confusing, especially due to a lack of knowledge of fungi. Research has implemented CNN to precisely identify 103 mushroom species from their natural habitat with a high accuracy of 96.7% [13]. This study is significant to mycologists, scientists, and the public in enhancing the safe consumption of mushroom species. Another study has also explored wild mushrooms in their natural habitat with the Mobilenetv2 detection model [14]. The result shows that the performance of the classification has been high with 97.89% accuracy. Table 1 shows the latest comparisons of similar works using CNN-based models.

Other studies include a project by [15], which presents an intelligent system for cultivating and classifying mushrooms using CNN to determine edible mushrooms based on an image scan. The experimental results show that the system works with an accuracy rate of 72%. The study by [16] has discussed the use of machine learning algorithms, specifically the YOLOv5 algorithm, for the detection of Macrolepiota Procera mushrooms in precision agriculture. According to the experimental findings, their first model in the research had the best accuracy, with an F1 score of 98 percent at 1200 epochs and a precision of 97%. Another study by [17] discusses the identification of wild mushrooms based on ensemble learning. The study focuses on the mushroom resources in Yunnan Province, China, which has abundant wild mushroom resources. The researchers collected data on wild mushrooms in multiple scenes and trained VGG16, Resnet18, and Googlenet models using the bagging algorithm. The integrated model showed better performance compared to a single CNN, with an accuracy of 93.1%. Meanwhile, a study by [18] discusses the development of a smart mushroom grading system for grey oyster mushrooms. The traditional classification system used by agricultural farmers in Malaysia is based on manual eye observation. The article proposes the use of image processing and deep learning, specifically convolutional neural networks (CNN), for intra-class classification of grey oyster mushrooms. The VGG16 pre-trained network model is studied and utilized in this research. This preliminary study shows that the VGG16 could perform well in a simple classification analysis with 96.7% accuracy in training and 90.0% in the testing stage. The study by [19] discusses the challenges of using a deep learning CNN for mushroom image classification. The authors propose a new mushroom image dataset called MO106, which contains 106 species on 29,114 images. They analyze the usage of EfficientNet networks for mushroom image classification and compare different training strategies. The best approach achieved 92.6% accuracy on the dataset. It was chosen for the mushroom image classification task because of its ability to achieve high accuracy while minimizing computational resources.

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Based on the previous good performance of CNN and its model variants, this study has chosen to further explore the standard CNN algorithm for this particular research project. It is expected that CNN could also generate acceptable performance for this study, which is to be used on the mobile platform. The standard CNN algorithm will be explored in terms of its accuracy and capability in this classification problem based on the mobile platform. The performance result in this study is expected to be on par with the exceptional results of the previous studies.

Table 1. Among the latest similar works using various models of CNN

No	Algorithm	Objective	Problem	Result	References
1	1D- CNN	To classify deadly and edible mushrooms	Difficult to identify complex patterns in mushroom appearances	High accuracy, highly reliable in classification	[9]
2	DenseNet - 121	To enhance the precision and reliability of mushroom classification	Difficult to classify edible and toxic mushrooms due to similarities in appearance	Achieved 97% for almost all metrics. The improvements increased precision and recall.	[10]
3	Vision Transformers (ViTs) and ResNet models	To find the most suitable architecture for mushroom identification in Malaysia	Lack of knowledge in identifying mushrooms	The ViT-L/16 model achieved the highest accuracy at 90.47%	[11]
4	Resnet50, YoloV5. Alexnet	To identify the difference between toxic and edible mushrooms	Challenging to distinguish toxic and non-toxic mushrooms	The deep learning models produced acceptable accuracies	[12]
5	CNN	To enhance the safety of eating mushrooms by ensuring accurate mushroom identification	Limited knowledge in classifying mushrooms from their natural habitat.	Accuracy of 96.70% with high precision, recall, and F1 score	[13]
6	Mobilenetv2	To identify the most effective technique for categorizing mushrooms	Difficult to classify mushrooms in their natural habitat	Accuracy was 91%	[14]

2.2 Convolutional neural network (CNN)

The CNN algorithm is a deep learning model developed primarily for processing and analyzing visual data, such as photographs. It is a specific type of neural network design that uses convolutional layers to efficiently extract hierarchical information from input images. This algorithm specializes in deep feedforward networks. The fundamental structure consists of one or more convolutional layers, pooling layers, full connection layers, and an output layer. A basic CNN learner is an autonomous CNN that automatically extracts visual features. In comparison to manual picture feature selection, labelling, and recognition, CNN is more efficient, convenient, quantifiable, and self-adaptive [17]. CNN uses convolution to extract features from mushroom photos. CNN's general structure has three layers: input, middle, and output. Specifically, the input layer, or the first layer of a CNN, is often made up of the convolution layer, which receives pictures. The middle layer often consists of convolutional, full-connection, or pooling layers. The full-connection layer joins all features, whereas the pooling layer compiles the input feature graph. On the one hand, it reduces the size of the feature graph and lowers the network's computational complexity. On the one hand, feature compression is used to extract key features. The output layer often comprises the entire connection layer. It is used to send the output value of the classifier, which classifies the output value of the full connection layer [20]. To summarize, CNN excels in processing complex data, particularly in deep learning and image recognition applications. Convolutional, pooling, and fully connected layers provide a hierarchical structure, allowing these networks to effectively learn complicated patterns. Convolutional layers start by extracting features from RGB input images. Convolution layers are utilized to create a hierarchical knowledge of patterns, which is beneficial for tasks such as recognizing

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wallet properties. Pooling layers increase processing efficiency by lowering spatial dimensions, whilst the fully linked layer uses recovered features to achieve correct categorization.

3. METHODOLOGY

There are three main phases of the research methodology: data collection and preprocessing, model design and implementation, and model performance evaluation. The descriptions of each of the phases are given in each of the subsections. Fig. 1 shows the phases of the research methodology.

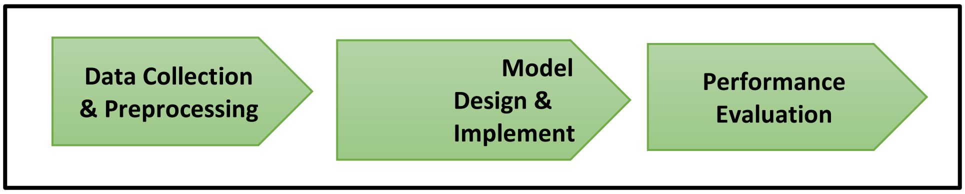

Fig. 1. Phases of the research methodology

3.1 Data collection and preprocessing

Data for this study were collected via Roboflow.com, a well-known online platform for datasets. The dataset utilized in this study was obtained from Roboflow's huge archive and was particularly chosen to correspond with the research focus on mushroom identification. The dataset contains a wide variety of mushroom samples, including different species, features, and classifications, making it a comprehensive resource for training and validating machine learning models. The decision to use Roboflow.com for data collection was motivated by the platform's reputation for hosting high-quality datasets and cultivating a collaborative data science community. The dataset in this study consisted of 2513 images, with 1360 poisonous and 1153 edible mushroom images.

Several pre-processing procedures were carefully carried out to improve the quality of the dataset and prepare it for thorough analysis. These procedures were essential for fine-tuning the dataset to guarantee peak performance when the CNN was trained with the intention of classifying mushrooms. Python was the tool of choice for carrying out these pre-processing operations because of its large library. Resizing images is the first step in the pre-processing phase of the mushroom classification project. Standardizing the size of the input images is a critical step that is undertaken to maintain uniformity across the dataset and to reduce computing complexity. Next, normalization is to achieve the common scaling of the pixel values in the images from the dataset. By adjusting the input pixel values to fall between 0 and 1, this procedure aids in preserving consistency and enhancing the CNN model's productivity. This approach to normalization ensures that the dataset is in the optimal format for training a CNN model, thereby enhancing the overall efficiency and accuracy of the mushroom classification system.

3.2 Model design and implementation

System Architecture

The system architecture provides a visual representation of the mobile application's stages, beginning with user input and culminating in the system's output. This structured workflow ensures a rigorous approach to developing a reliable and accurate CNN model for mushroom detection, enhancing the usability of the application. As shown in Fig. 2, this architecture is specifically applied to the CNN-based mushroom detection model. The process begins with the Data Preprocessing Phase, where images undergo resizing to

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ensure uniform dimensions and normalization to standardize pixel values, which improves the model's training efficiency. The dataset is then split into three subsets: 88% for training, 8% for validation, and 4% for testing. This is the best split ratio that has been tested. The other data split ratios were 70:30 and 80:20. This division ensures that the model is trained on a substantial portion of data, validated on a smaller subset to tune parameters, and tested on an independent set to evaluate performance. The standard CNN algorithm has been used in this study. This is due to its simpler convolutional and pooling layers, which could lower the computational cost, suitable with the limitation of hardware specifications.

In this research, there are 2 classes, which are edible and poisonous for the CNN to classify. In the CNN Model Training Phase, convolutional and max pooling layers are used to extract features from pictures, followed by model evaluation and saving of the trained model. The Validation Phase consists of selecting the best-performing model, extracting features, and assessing the model's performance on the validation set. This step is critical for fine-tuning the model so that it generalizes well. The Testing Phase examines the selected model on the testing dataset, making any necessary parameter adjustments to improve performance. Finally, the verified and tested model is used in the Mushroom Detection Phase to determine whether mushrooms are poisonous or edible based on user-submitted images.

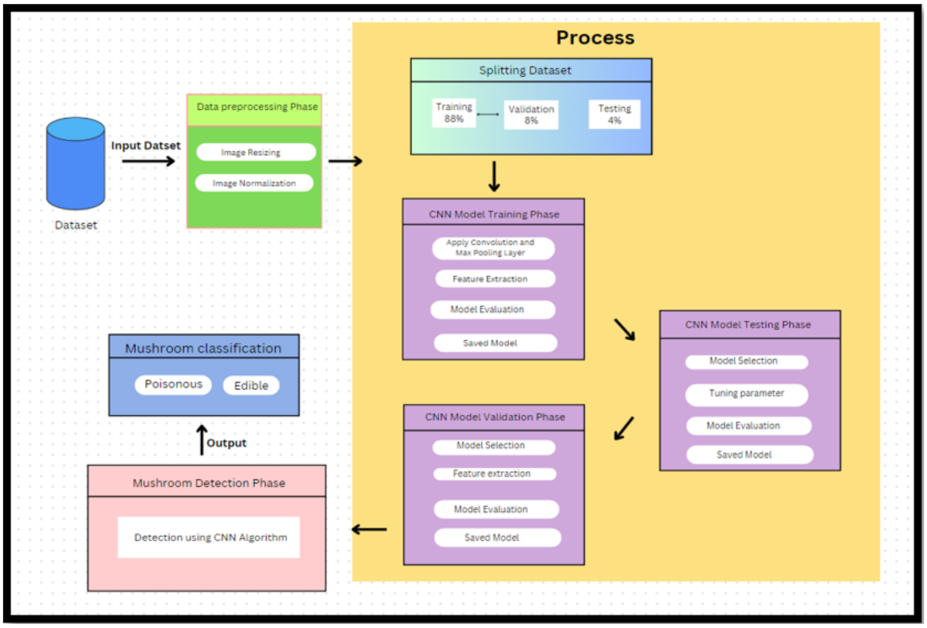

Fig. 2. The system architecture

Use Case Diagram

Use Case Diagrams are useful for depicting how users engage with a mobile application. These diagrams show the relationships between different user roles and the functionalities built into the mobile application. Developers obtain a thorough knowledge of the application's workflow by visualizing how users navigate and interact with various elements. Use Case Diagrams are useful for defining both the functional needs of a mobile application and the expectations of end users. This graphical depiction promotes successful communication across development teams, stakeholders, and designers, resulting in a common understanding of the application's functionality and user interactions. Fig. 3 shows the Use Case Diagram that will be used for the development of the mobile application.

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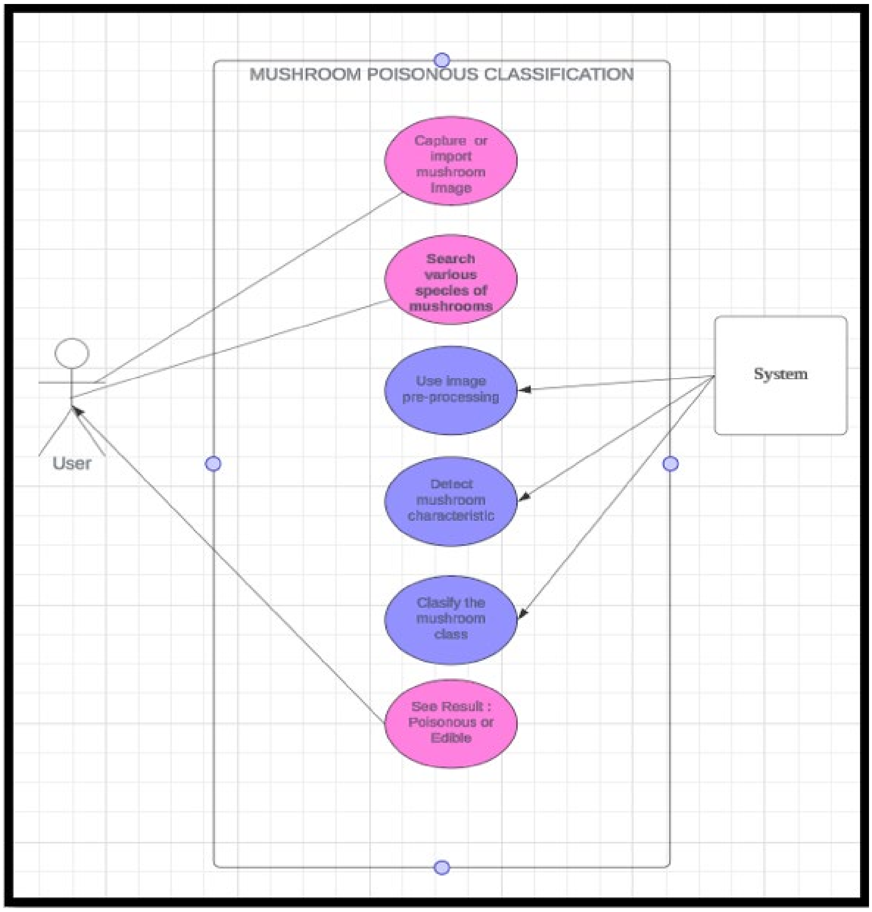

Fig. 3. Use Case Diagram of the proposed system.

3.3 Performance evaluation

In this study, the performance evaluation has started with the Hold-Out method, which splits the dataset into ratios. It is a simple technique to evaluate a machine learning model, where some data are used for the training part and the others are used for the model's performance evaluation. The dataset in this research is divided into 3 data split ratios for the training and testing of the CNN algorithm. The data split ratios are 70:30, 80:20, and 88:8:4**.** The purpose of the data split is for the model to be fairly evaluated, avoiding overfitting and underfitting. The training dataset is for the algorithm to learn the pattern in the classification, while the testing dataset is to measure the algorithm's ability to classify. The third data split ratio contains a validation portion, which is usually used to tune the hyperparameters and avoid overfitting. Based on the best data ratio split, the performance of CNN in solving this classification task is evaluated using the confusion matrix. A confusion matrix is a table that assesses the efficacy of a classification system. The confusion matrix, which is used to provide the classifier's measurement parameters, has four essential properties as follows:

TP (True positive): Total number of cases that were predicted as yes and were correctly predicted.
TN (True negative): Total number of cases that were predicted as no and were correctly predicted.

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FP (False positive): Total number of cases that were predicted as yes and were wrong predictions.
FN (False negative): Total number of cases that were predicted as no and were wrong predictions.

In a confusion matrix, the performance measurements include classification accuracy, precision, recall, and F1-score. It is calculated as given in the formula, as shown in Eq. (1) to Eq. (4). These parameters provide information about the algorithm's efficacy and efficiency. Table 2 shows the common parameters to be evaluated.

$$Accuracy = (TP + TN) / (TP + FP + FN + TN) \tag{1}$$

$$Precision = TP / (TP + FP) \tag{2}$$

$$Recall = TP / (TP + FN) \tag{3}$$

$$F1 = (2 \text{ x } precision \text{ x } recall) / (precision + recall) \tag{4}$$

Table 2. Common Parameters to be evaluated.

Parameter	Description
Accuracy	The overall correctness of the model's predictions
Precision	The ratio of correctly predicted poisonous mushrooms to the total predicted as poisonous
Recall	The ratio of correctly predicted poisonous mushrooms to the actual number of poisonous mushrooms
F1	The harmonic means of precision and recall, providing a balance between the two metrics

4. RESULTS AND FINDINGS

The CNN model was first evaluated by assessing its performance at three data splitting ratios: 80:20 for training and testing [21], 70:30 for training and testing [22], and 88:8:4 for training, validation, and testing [23]. The third data split included validation, which was optional, and the setting was acquired from Roboflow [23]. The Hold-Out method separates data into training, validation, and testing sets so that the model can learn, tune, and be fairly evaluated on the new data input. Each configuration was examined for 20 epochs to ensure consistency in the evaluation process. The goal was to find the ideal ratio for balancing training, validation, and test data, guaranteeing that the model achieves high accuracy and generalizes efficiently to new data. The data of the three splitting ratios are recorded in Table 3.

Table 3 shows the performance of the CNN model using three data splitting ratios: 80:20 for training and testing, 70:30 for training and testing, and 88:8:4 for training, testing, and validation. The model achieved a test accuracy of 81% and a model accuracy of 61% with the 80:20 split. The 70:30 split resulted in the highest test accuracy of 85% and a model training accuracy of 59%. The 88:8:4 split yielded the highest model accuracy during training at 89%, with a test accuracy of 74%, demonstrating performance by training, testing, and validation.

For each model split, 20 epochs were used, with early stopping to prevent overfitting. Early stopping checks the validation loss and stops training when no improvement is seen after a set number of epochs, ensuring that the model does not overfit the training data. This strategy helps to retain the model's generalizability and keeps it from getting overly specialized in the training data, which can result in poor performance on new, unseen samples. Furthermore, training logs contain useful information about the model's performance at each epoch. For example, in the early epoch, the training loss is greatly reduced, while validation accuracy rises continuously. As training advances, both training and validation accuracy approach their peak values, and the validation loss stabilizes, showing that the model is learning efficiently

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and generalizing well. The thorough epoch-by-epoch analysis demonstrates how the model evolves, emphasizing the efficiency of the specified parameters and training procedures.

Table 3. Data splitting ratio and results

Data Splitting Ratio	Test Accuracy	Model training accuracy
80:20	81%	61%
70:30	85%	59%
88:8:4	74%	89%

4.1 Graph analysis

A graphical analysis of the training and validation (testing) accuracy over epochs for each data split reveals critical information about the model's learning process. The training accuracy curves regularly showed high values, showing that the model learned well from the training data. In contrast, the validation or testing accuracy curves demonstrated the model's capacity to generalize to previously encountered data.

Additionally, the convergence of these curves indicates that the model balances fitting the training data and achieving good results on fresh, untested samples, preventing overfitting. For the model to be resilient and reliable in real-world applications, this balance is essential. These curves' thorough analysis aids in spotting possible training-related problems, such as underfitting or overfitting, and enables modifications to be made to enhance the performance of the model. Fig. 4, Fig. 5, and Fig. 6 show the graph representation of the model split over epochs.

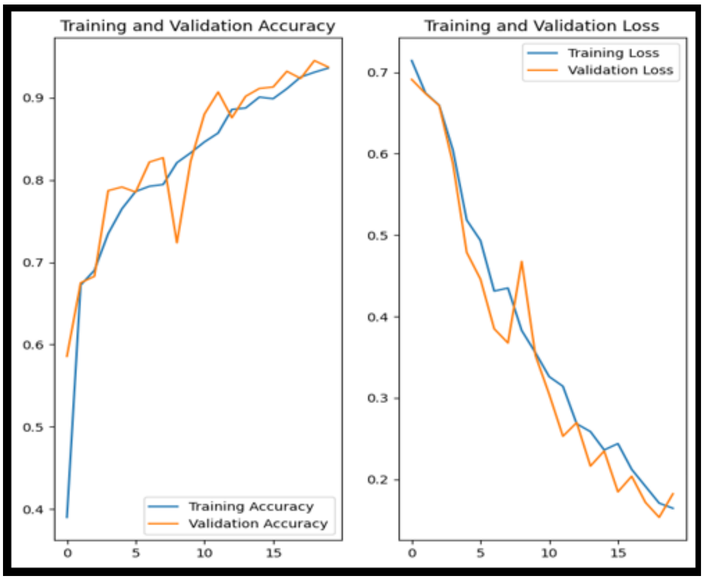

Fig. 4. Graph of 80:20 model split

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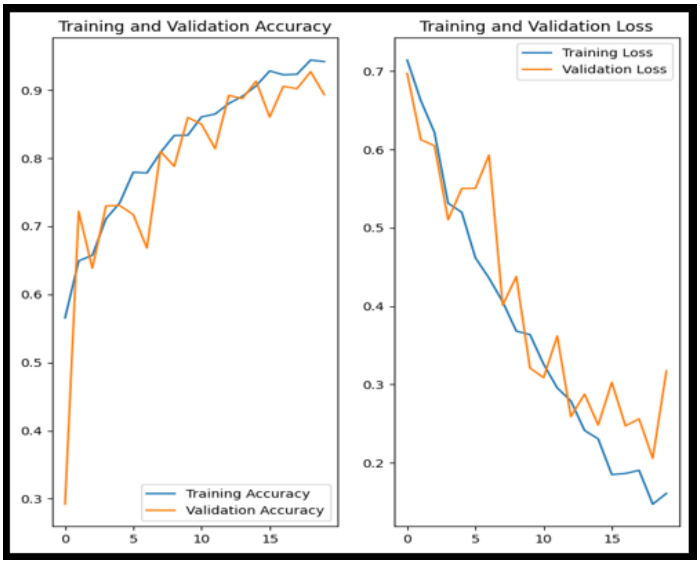

Fig. 5. Graph of 70:30 model split

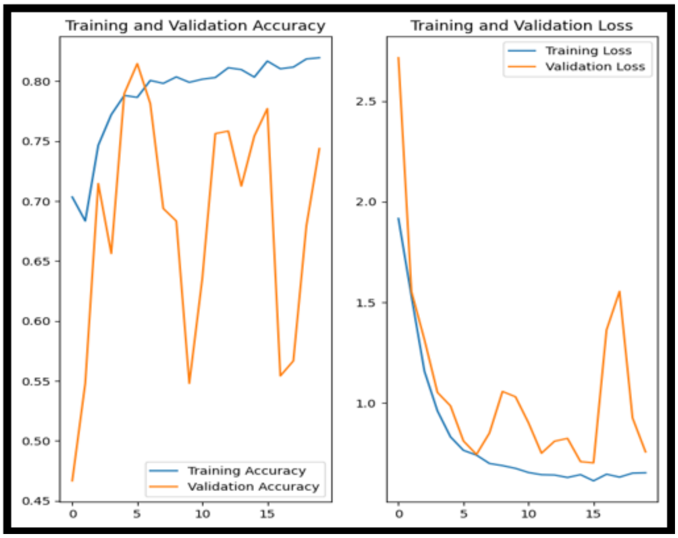

Fig. 6. Graph of 88:8:4 model split

The three sets of graphs illustrate the training and validation accuracy as well as the training and validation loss over epochs for different model runs. Through the graphs, the learning progress of the algorithm could be analyzed over the epoch. Fig 4. shows that the accuracy is increasing with the number of epochs. Based on Fig. 4, it can be seen that the validation data results are a bit higher than the training results. However, the gaps are small, and this still shows the good model performance results. Fig. 5 graph also shows an increase in accuracy, but with more fluctuations in the validation accuracy, suggesting some variability in the model's generalization ability. This model is still considered to have good performance

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with the small gaps between training and testing results. Fig. 6 graph highlights a significant rise in the training accuracy with unstable fluctuations in validation accuracy and loss. Even though the graph shows that the model is unstable, the data split of 88:8:4 has been chosen for the model due to its good performance when deployed on the mobile platform. This data split has also been recommended in the Roboflow project [23]. Overall, across all graphs, the loss curves consistently decrease, showing effective learning of the model, although performance of the recognition and classification varies between models. There are no critical underfitting or overfitting issues in these performance evaluations.

4.2 Confusion matrix results

A confusion matrix is used in the accuracy testing of the mushroom detection system to assess how well the model performs in identifying mushrooms as edible or toxic. Four essential metrics are included in this matrix: True Negative (TN), False Positive (FP), True Positive (TP), and False Negative (FN). Here, "TP" denotes that the model properly identifies edible mushrooms, but "FP" denotes situations in which the model wrongly labels edible mushrooms as poisonous. TN indicates the accurate identification of toxic mushrooms, while FN indicates instances in which the model fails to identify poisonous mushrooms and classifies them as edible. By analyzing these metrics, the confusion matrix offers useful insights into the accuracy and dependability of the model. Fig. 7 shows the confusion matrix of the model with the results of the testing from the 88:8:4 model split. The data split of 88:8:4 has been chosen due to its acceptable performance during training and testing. However, this model has been chosen mainly because it has shown good performance in image recognition and classification on the mobile platform compared to other data splits. The data split has been recommended in the Roboflow project [23].

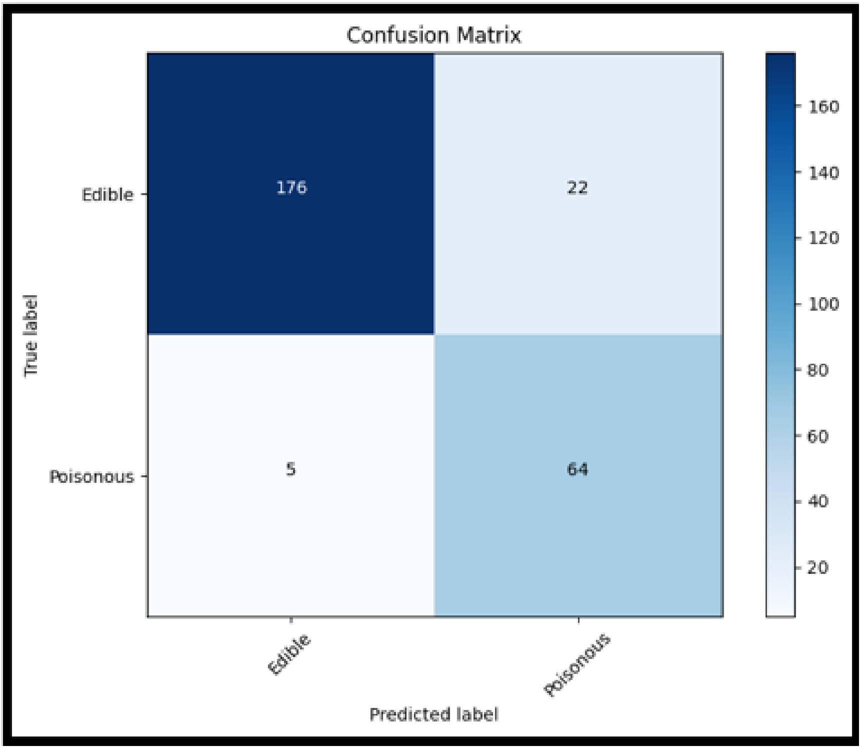

Fig. 7. The confusion matrix

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The performance of the CNN-based mushroom detection system is demonstrated by the given confusion matrix, which emphasizes the system's capacity to categorize mushrooms as either edible or poisonous. The matrix demonstrates the model's strong capacity to successfully recognize edible mushrooms, with 176 edible and 64 poisonous mushrooms correctly identified. However, it did erroneously classify 22 poisonous mushrooms as edible and 5 edible mushrooms as poisonous, indicating opportunities for improvement in lowering false positives and false negatives. Overall, the confusion matrix shows how well the model works for classifying mushrooms, but it also highlights areas that still require improvement to enhance the model's accuracy and dependability. The dataset used for training and testing consists of 2513 images, providing a basis for evaluating the model's accuracy and reliability.

The segment code in Fig. 8 demonstrates the manual calculation of the accuracy, precision, recall, and F1 score for the CNN model based on the confusion matrix values provided. The true positive (TP) count is 64, the false positive (FP) count is 22, the false negative (FN) count is 5, and the true negative (TN) count is 176. These values are used to compute the four key performance metrics. All the components of Figure 9 are well defined in Table 4 to improve the understanding of the model.

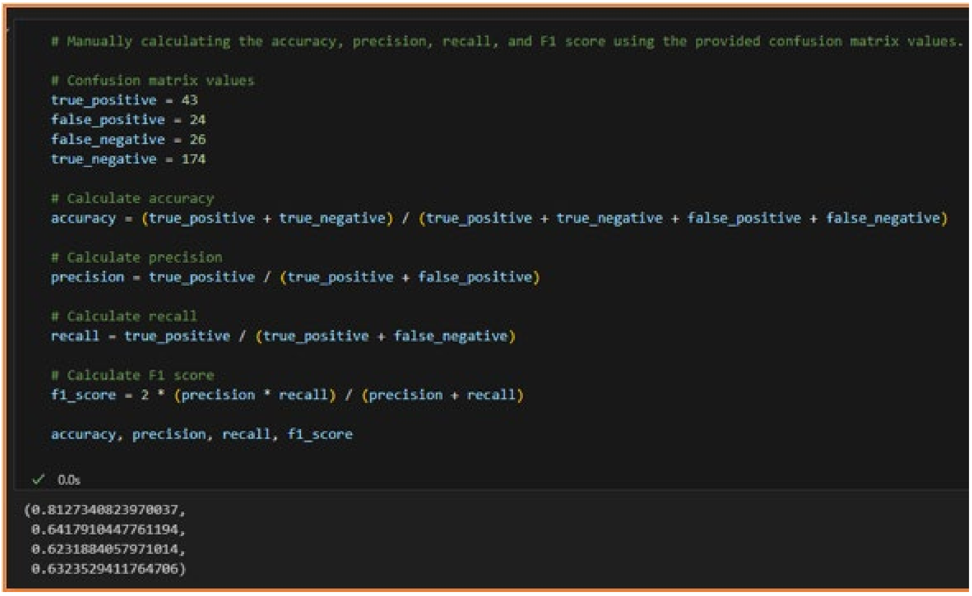

Fig. 8. The segment code for manually calculating the accuracy of the CNN Model

Table 4. Calculation of accuracy, Precision, recall, f1 score

	Percentage
Accuracy	89%
Precision	74%
Recall	93%
F1 Score	83%

The accuracy, precision, recall, and F1 score are computed based on these variables to assess how well the CNN model performs in the categorization of mushrooms. The CNN model's total accuracy is found to be 0.89, meaning that 89% of its predictions come true. The precision of the model is 0.74, meaning that 74% of the samples that the model classified as edible were actually edible. Additionally, the recall for the edible class is 0.93, indicating that when a sample is predicted to be edible, the model correctly recognizes

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edible mushrooms 93% of the time. The F1 score for the edible class is 0.83, providing a balanced measure of the model's performance for this class. The dataset employed in this project, which only contains 3726 photos, contributes to the project's 89% accuracy score. To reach an accuracy of more than 90%, a substantially bigger data set is needed, preferably ten thousand photos. However, in this study, CNN can recognize and classify poisonous and edible mushrooms. The feature hierarchy extraction, combined with spatial invariance and parameter sharing, makes CNNs very useful for image-related tasks, such as picture classification and object detection [8]. The algorithm's capacity to detect detailed patterns at various levels of abstraction, as well as its resilience to changes in spatial placement, contribute to its extensive use in computer vision applications [24].

4.3 Comparison between similar works

The comparison of performance between similar works has been made, and the results are shown in Table 5. The proposed model has been compared with the standard CNN and with other CNN based pretrained models; DenseNet, AlexNet, and Mobilenet. Based on the previous research, most of the models' accuracy results are more than 90%. Only AlexNet has generated a lower result in the mushroom classification problem [12]. In this research, the result obtained is still acceptable with an accuracy of 89%. This shows that the proposed model can generate good results in this recognition and classification problem. However, the accuracy might be increased with the improvement done to the dataset, such as applying data augmentation and balancing the poisonous and edible data.

Table 5. Comparison of accuracy between similar works

References	Algorithm/Model	Accuracy
[10]	Dense Convolutional Network (DenseNet)	90%
[12]	AlexNet	79%
[13]	CNN	96.7%
[14]	MobileNet	91%
Proposed model	CNN	89%

4.4 Mobile application user interface

To provide users with a seamless experience when identifying mushrooms, the mobile application has an intuitive and user-friendly user interface. The app's main screen has clearly labelled buttons that walk the user through its main features. Users have a choice on how they input photographs for mushroom identification, with options to "TAKE A PHOTO" and "SELECT AN IMAGE FROM GALLERY" at the top of the screen. The meaning of these options is readily apparent to users due to their unambiguous marking with mushroom symbols, which also improves visual attractiveness. The detail of the interface is shown in Fig. 9. The "History" button, which is located beneath these options, enables users to view a history of their prior interactions and identifications. For users who want to go back and learn from their previous identifications, this tool is essential. Additionally, there is an "ENCYCLOPEDIA" button that leads to a thorough database of mushroom species. This encyclopedia provides in-depth details on a variety of mushrooms, making it an invaluable educational tool. The "Home," "Encyclopedia," and "Profile" sections can be quickly accessed via the navigation bar at the bottom of the screen, which makes navigating the program simple. Fig. 10 shows the sample of poisonous mushroom detections, while Fig. 11 shows the sample of edible mushroom detections.

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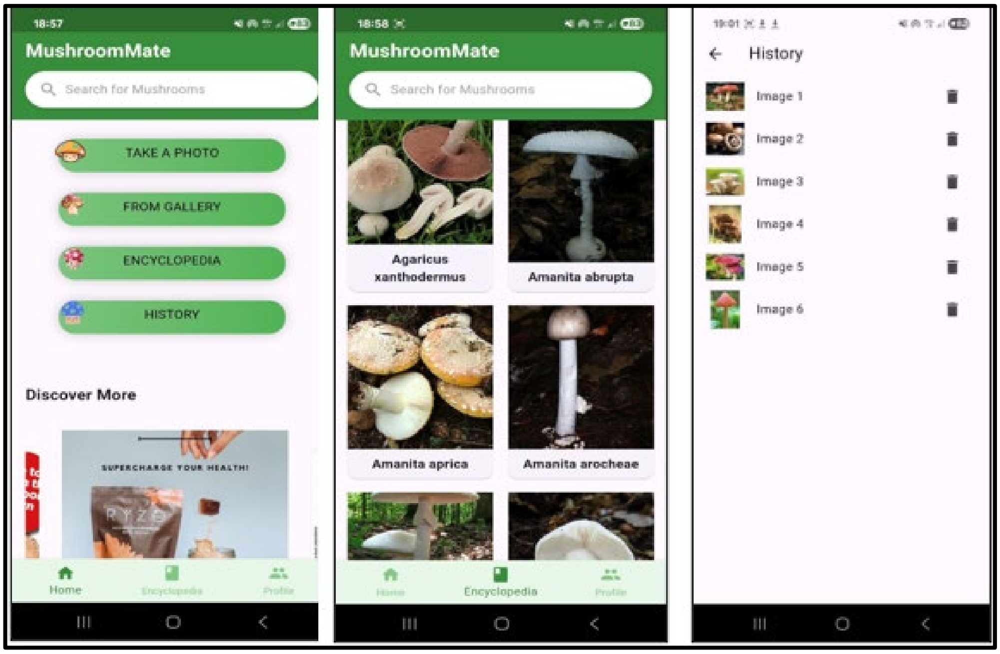

Fig. 9. User interface for home, Encyclopedia and History of the mobile application

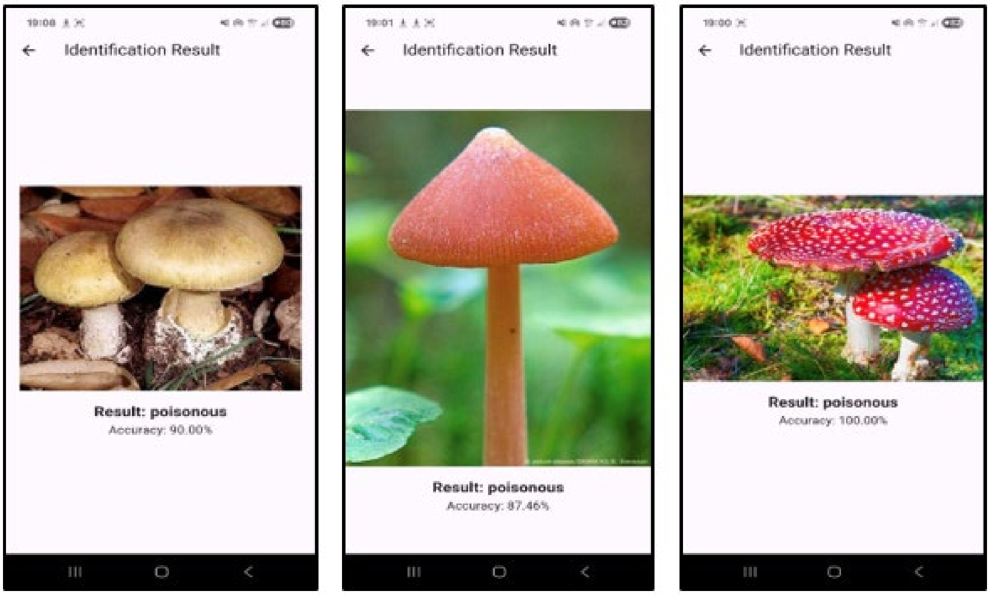

Fig. 10. Sample of poisonous mushroom detections with their accuracies

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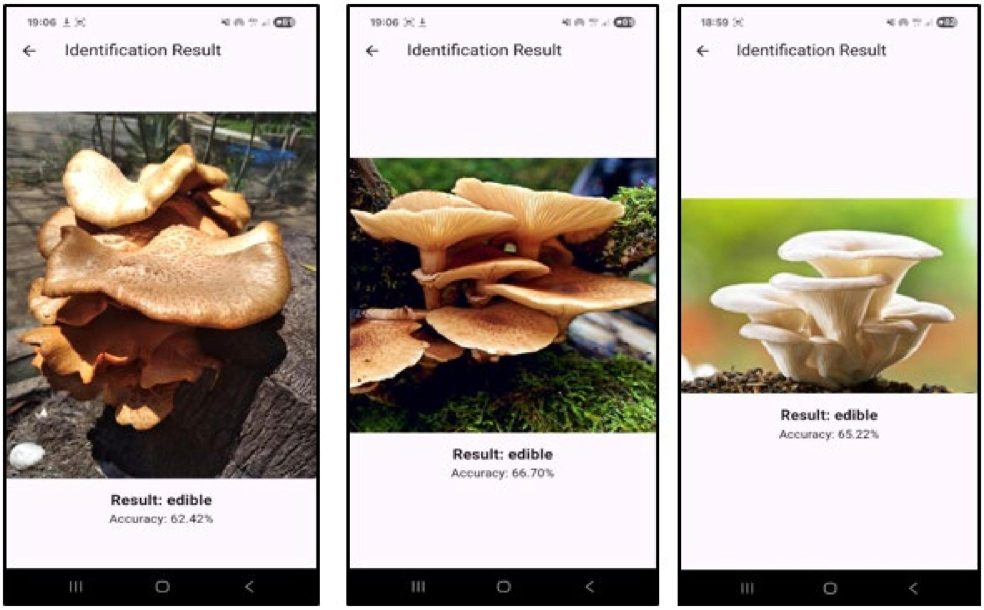

Fig. 11. Sample of edible mushroom detections with their accuracies

5. CONCLUSION AND RECOMMENDATION

In conclusion, this study has created a mobile application that uses the CNN algorithm to detect poisonous mushrooms. The research successfully completed its main goal, which is to classify the poisonous and edible mushrooms using CNN algorithm on a mobile platform. Attaining an accuracy rate of 89%, the CNN model showed a reliable degree of accuracy in differentiating between poisonous and edible mushrooms. The research project shows how CNN algorithms may be used practically in real-world situations, which makes a substantial contribution to the field of mobile apps. It demonstrates how cutting-edge machine learning models can be seamlessly incorporated into a simple mobile interface, offering a useful tool for mushroom identification and safety. The significance of this project lies in its multifaceted impact on both individual users and communities, offering a comprehensive solution to the crucial challenge of mushroom and plant identification. By providing a user-friendly platform for identifying mushrooms, including potentially harmful varieties, the research project ensures the safety and well-being of a diverse range of users, from foragers and hikers to gardening enthusiasts and culinary explorers. Moreover, serving as an educational resource, the project fosters heightened awareness of plant characteristics and associated risks, empowering users to make informed decisions regarding plant care and safety. This dual emphasis on users' empowerment and safety not only enhances the overall quality of interactions with the natural world but also cultivates a sense of responsibility and environmental consciousness within communities, promoting a harmonious coexistence between individuals and their surrounding ecosystems. Additionally, the project aligns with the United Nations' Sustainable Development Goal (SDG) 15, Life on Land, by promoting the sustainable use of terrestrial ecosystems, combating desertification, and halting biodiversity loss, further contributing to the global efforts of preserving and restoring the planet's biodiversity. The limitation in the study is the potential for misclassification due to similar visual features between poisonous and non-poisonous mushrooms. While the CNN model is trained to differentiate based on visual cues, certain species may have small differences that are challenging to capture accurately. Therefore, the future work is to improve the accuracy and robustness of the model, which would be increased by broadening the training

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dataset to include a wider range of mushroom species and more varied environmental circumstances. Enhancing the comprehensiveness of the dataset by collaborating with mycologists and field experts to obtain high-quality photos and annotations can improve model performance. This initiative establishes a standard for future advancements in related applications and emphasizes the value of fusing mobile technology and machine learning to solve real-world issues.

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7. CONFLICT OF INTEREST STATEMENT

There is no conflict of interest in the research.

8. AUTHOR'S CONTRIBUTIONS

Shazlin Nizam Amirul: Research and development, writing report; **Norlina Mohd Sabri**: Supervised, writing first draft; **Gloria Jennis Tan**: Review draft; **Nurul Ainina Redwan**: Editing, review; **Zhiping Zhang**: Final review.

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