Journal of Engineering Science and Technology
Special Issue on ICITE20222, November (2022) 1 - 16

NEURAL NETWORK APPROACH FOR BIVALVES CLASSIFICATION

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Abstract

The deep learning approach has demonstrated outstanding performance in detecting and classifying marine organisms such as marine bivalves. Bivalves, such as oysters and clams, have two-valved shells that contain soft-bodied invertebrates. Understanding the diversity of bivalves is essential as they play a vital role in the coastal ecosystem. These species were considered one of the world's threatened species groups. However, marine bivalves face significant exploitation in coastal regions, leading to the endangerment of certain species. Thus, this paper introduces an accurate classification method for marine bivalves. Numerous bivalve images were collected from the coastal area in the northwestern region of Bohol, Philippines, and subjected to image preprocessing techniques to enhance the model's effectiveness. Three deep learning methods, namely MobileNetV2, EfficientNetB4, and ResNet50 architecture, were employed to construct the neural network model for classification. These models utilize complex algorithms to learn and identify patterns and features within the bivalve images, enabling accurate classification. The results of the experiments reveal that EfficientNetB4 achieves higher accuracy in bivalve classification. The implemented model attains a classification accuracy of 97.29%, a recall rate of 97.04%, and precision and F1-score of 97.46% and 97.025%, respectively. In conclusion, the EfficientNetB4 model exhibits significant potential in accurately classifying marine bivalves.

Keywords: Bivalves, Convolutional neural network, Deep neural network, Image classification.

1. Introduction

Marine bivalve is one of the essential elements playing significant roles in the freshwater ecosystem [1]. Bivalves, such as oysters and clams, have two-valved shells that contain soft-bodied invertebrates [2]. Throughout history, bivalves have held significant significance in coastal communities in cultural and economic terms. The marine bivalves are crucial resources that coastal communities heavily rely on, particularly for sustenance and livelihood [3]. However, these species are considered one of the world's most highly threatened and near threatened [4]. The marine bivalves are also considered highly gleaned. They are also considered highly gleaned species in coastal communities. Studies reveal that there has been a decreased abundance of bivalves in the coastal ecosystem in the past years [5]. Bivalves are considered highly threatened species due to anthropogenic activities and natural disturbances. They continue to lose their rich biodiversity resources, leading to global decline and causing conservation and social concern. Community awareness plays an essential role in the protection of bivalves. Hence, this study aims to classify the marine bivalves in the Northwestern part of Bohol, Philippines. This study seeks to raise awareness among the local community regarding the presence of highly endangered and vulnerable bivalve species in their vicinity. The classification process will allow for a more comprehensive understanding of the bivalve population and identify specific species at greater risk of extinction. By providing this information to the community, the study aims to foster a sense of awareness and responsibility toward the conservation and protection of these bivalves, ultimately contributing to their long-term survival.

The classification of marine organisms such as bivalves is an essential tool for understanding the components of their biodiversity. Traditionally, the process of classification of bivalves has been done by looking at species' morphological features, which requires expertise and knowledge in the field. Examining the morphological features of bivalves, such as the body's shapes, colours, and size, helps to provide a reliable classification of the species. However, examining the morphological features to classify the bivalves manually consumes a lot of time and effort, especially with many datasets. To overcome these challenges, the need for the development of an automated image-based system for classification using artificial intelligence (AI) is an essential tool. The development of an AI classification system for bivalve classification addresses the limitations of manual classification, offering a more efficient and effective approach to studying and categorizing these organisms [6].

2. Related Works

In the past years, the application of artificial intelligence has shown much-growing interest in many applications. One of its applications is in the field of bioinformatics. Bioinformatics is the study of the application of information technology to the area of biology [7]. This field is commonly used to analyse large amounts of biological data and provides valuable insights [8]. Various computational technologies and algorithms are used to extract knowledge encoded in biological data. Artificial intelligence offers a powerful approach to extracting knowledge from biological data [9]. One of the artificial techniques is the artificial neural network commonly used in image recognition. It can capture and represents input and output relationship among data [10]. Therefore, the application of image recognition in classifying marine bivalves species could be possible.

The deep learning approach is a branch of machine learning in artificial intelligence. This approach provides a hierarchical representation of data through convolutions and allows data representation through several levels of abstraction [11]. A convolutional neural network (CNN) is a type of deep learning approach that is specialized for image recognition [12]. One of the essential aspects of CNN is minimizing the number of parameters in ANN and obtaining the abstract features when input propagates toward the deeper layers [13]. It allows the users to encode image features into the architecture, making the network more suited for image-focused tasks and reducing the parameters required to set up the model [14]. The application of CNN has been used in various fields, including image processing, object detection, image painting, and super solution [15]. CNN is made up of convolutional neural layers, pooling layers, and fully connected layers. These layers of CNN transform the input volume to an output volume of neuron activation leading to the final fully connected layers, which result in mapping the input data to a 1D feature vector [16]. The attractive feature of CNN is its ability to exploit spatial or temporal correlation in data [17]. With these features, it has been found that CNN is considered the best algorithm for understanding image content and has shown highly effective performance, particularly in classification [18].

Studies show that CNN performs exemplary in classification, image segmentation, image detection, and other related tasks [16]. Several researchers have used deep learning in classification problems wherein the dataset of images were the photographs of the entire organism/plants. The CNN model was used in the good and bad green coffee bean classifications, which yields approximately 93.34% accuracy [19]. The utilization of a deep learning approach for recognizing fruits has shown consistent correct and consistent findings wherein the model utilizes EfficientNet design for identifying fruit [20]. The CNN model was also used to classify occasional quality beans in mobile systems, wherein ResNet has shown the highest accuracy in classifying the quality of beans compared to VGG-16 [21].

Moreover, CNN was used to create a robust neural network architecture that can classify millions of benthic fauna images and obtain a model accuracy comparable to human classifiers [22]. The CNN model has also been successfully applied in classifying coffee bean defects, resulting in correct classification [23]. A pre-trained CNN model has been used to recognize different taxonomic groups of microfossils, correctly identifying those species [24]. The convolutional neural network has been applied in the image classification of phylogenetic relationships of bivalves, wherein thousands of images of bivalves were trained and used to detect relationships among bivalves based on their similarities [25].

The main contributions of the paper are as follows: A classification of the marine bivalves using three state-of-the-art architecture neural networks models such as MobileNetV2, EfficientNetB21, and ResNet50 is developed. A dataset comprised of 12 threatened marine bivalves was collected from the assessment results in the vicinity area. A multi-layer neural network model is utilized for the classification. A comparison of the performance of the model using four performance metrics. Integration of the optimal model into the mobile application is used as a tool to classify the marine bivalves.

Aiming for the accurate classification of the marine bivalves, this paper introduces the comparison of the three deep learning methods, MobileNetV2, EfficientNetB4, and ResNet50 Architecture, to classify the highly gleaned marine bivalves in the coastal area in the Northwestern part of Bohol, Philippines. The three neural network architectures were evaluated based on their performance metrics. Various images featuring the marine bivalves were utilized for training, testing, and validating the CNN model. The optimal CNN model is deployed into a mobile application allowing the user to classify the said species.

3. Problem Statement

Bivalves have significant functions in ecosystems as they contribute to nutrient cycling, create habitats, and filter water. These species face significant exploitation in coastal regions, leading to the endangerment of certain species. In order to study ecological processes and interactions, it is important to have a clear understanding of the distribution and abundance of various threatened bivalve species. However, traditional methods of species identification can be slow and require taxonomic expertise. Accurate identification of bivalve species is essential for their effective conservation and management since different species can have different ecological roles, distribution patterns, and conservation statuses. In this context, neural network-based classification can help classify threatened, endangered, or invasive species, aiding in conservation efforts.

4. Methods

This section describes the neural approach model for bivalves' classification. It comprises data collection, preprocessing, development of a neural network model, and model evaluation, as depicted in Fig. 1.

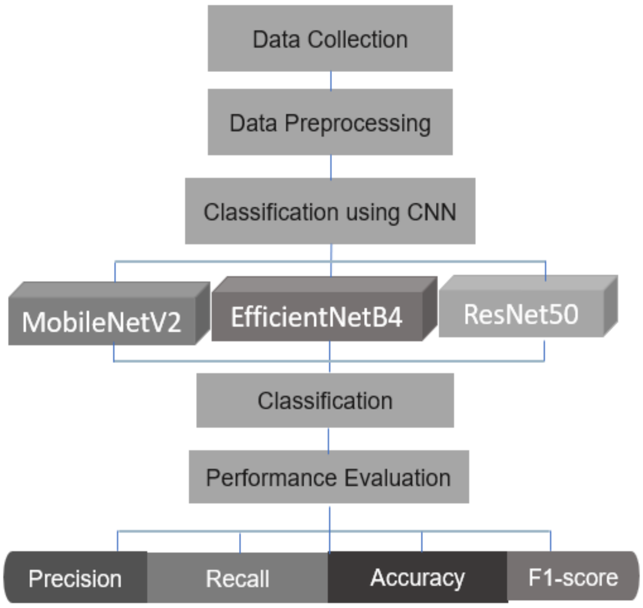

Fig. 1. Process flow diagram.

4.1. Data collection

The availability of the dataset must be comprehensive and well-designed for any classification problem. The inputs of the neural network were the images of different bivalves. This dataset was collected based on the assessment conducted in the coastal area of the Northwestern part of Bohol, Philippines. Various images from the different bivalves species were collected using a digital camera and smartphones. The dataset comprised 12 species of bivalves: *Anadara granusa*, *Anomalocardia squamosa*, *Circe scripta*, *Crassostrea iredalei*, *Gafrarium tumidum*, *Geloina erosa*, *Isognomon ephippium*, *Kataleysia recens*, *Lutaria philippinarum*, *Scapharca cornea*, *Tapes literatus*, *and Tellina staurella* as depicted in Fig. 2.

Fig. 2. List of dataset.

These identified species were considered threatened bivalves that were used for food consumption and a major source of livelihood [26]. An average of 800 images of each species were collected, as shown in Fig. 3. Some marine biologists validated the scientific name of the collected images of bivalves. All the bivalves are captured individually without interference from the other bivalves. These bivalves were collected in the coastal area of the northwestern part of Bohol, Philippines, particularly in Clarin, Tubigon, and Inabanga.

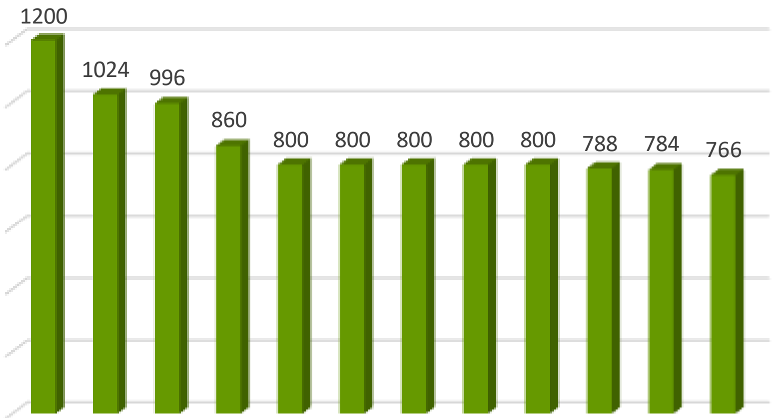

Fig. 3. Number of dataset per class.

4.2. Data preprocessing

Image Characteristics: The dataset comprises images of bivalves that were mostly captured using digital and mobile cameras. All the images collected do not have a uniform background since it was captured in the area where it was collected. These images served as the training input for the CNN model after being scaled to a fixed length and width image. In the data preprocessing stage, the images were resized into 224 x 224 pixels in three RGB colour channels compatible with the models' input layer.

Splitting of datasets: The dataset of the marine bivalves was split into three subsets for training, validation, and testing data. This dataset's images comprised 60% of the training, 20% of the validation, and 20% of the testing data. Training data was used for the training of the neural networks. The transition of the classification accuracy in the neural network's learning phase was verified using the validation data. At the same time, the testing data was used to assess the performance of the neural networks.

4.3. Neural network model for classification

This paper aims to classify the highly gleaned bivalves. Integrating a deep learning model into a mobile application is a potential tool for accurately classifying the said species. Three deep convolutional neural networks were utilized and compared in classification and image processing. The three state-of-the-art architectures: MobileNetV2, EfficientNetB4, and ResNet50, are compared in terms of performance, as displayed in Fig. 4. These three neural network architectures will be evaluated based on their performance metrics. The optimal neural network architecture will be integrated into a mobile application.

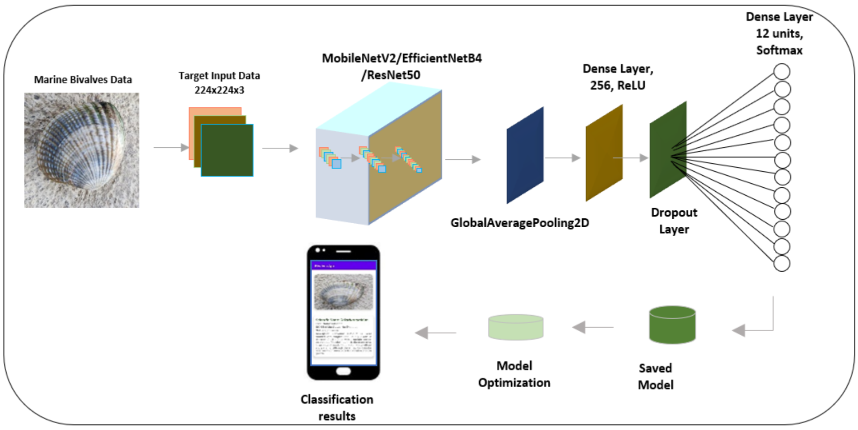

Fig. 4. Network architecture and model implementation.

CNN is a type of feedforward artificial neural network [27]. It aims to find effective features inside an image rather than working with an entire image. The CNN mainly consists of three layers, as shown in Fig. 5.

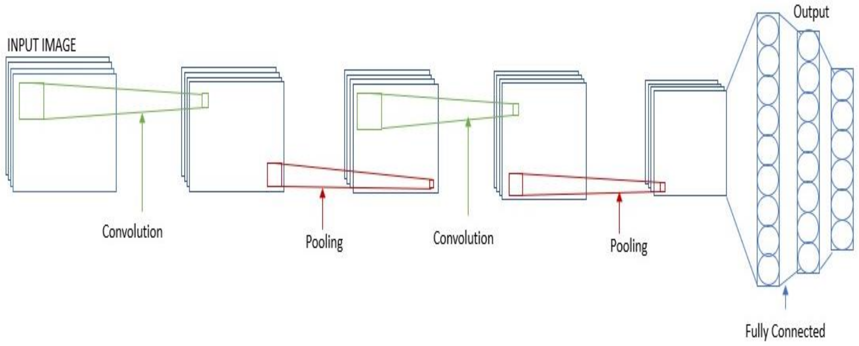

Fig. 5. Typical structure of CNN.

MobileNet is a type of convolutional neural network architecture (CNN) developed by Google researchers. MobileNets are designed to maximize the accuracy of a mobile device effectively [28]. MobileNetV2 is an improved version of MobileNetV1. These versions retained the separable convolution as the core layer but with fewer parameters to train than the full convolutional [29]. The updates on MobileNetV2 are bottleneck layers and shortcut connections [30].

The MobileNetV2 consists of 19 layers; the middle layer is used for feature extraction, while the last layer is used for classification. In this paper, as displayed in Fig. 4, the based layer of the MobileNetV2 was removed using (include top=False), and a new trainable layer was added. There are 19 bottleneck layers in MobileNet v2, consisting of three convolutional layers, namely, 1x1 convolution, 3x3 depth-wise convolution, and 1x1 pointwise convolution [31]. In the base model, ImageNet is used as a fixed feature extractor. After the extraction of the features from the input image, the extracted feature maps' size was reduced using the Global Average Pooling. The dropout layer was also used to ignore the overfitting of the model with the dataset. The ReLU activation function is used in the hidden layer; meanwhile, the SoftMax activation function is utilized in the entire link layer. A more detailed view of the MobileNetV2 model is depicted in Table 1.

Table 1. Summary of the proposed MobileNetV2 architecture.

Layer (type)	Output shape	No. of parameters
Mobilenetv2(*Functional*)	7×7×1280	2257984
GlobalAveragePooling2D	1280	0
dense (ReLU classifier)	256	327936
Dropout (Dropout)	256	0
dense (Softmax classifier)	12	3084

EfficientNet was developed to improve the performance of the Convolutional Neural Network and achieve state-of-the-art performance on ImageNet. It is a scaling technique that applies a compounded coefficient to uniformly scale up the dimensions of depth, width, and resolution and to scale up the baseline of EfficientNetB0 to the EfficientNetB7 series network [32]. As an alternative to the Rectifier Linear Unit (ReLU) activation function, Swish was utilized in the EfficientNet architecture as the new activation function. In this paper, the

EfficientNetB4 model was also used as the backbone architecture for the classification of bivalves. The base layer of EfficientNetB4 was also removed, and a new trainable layer was added to the architecture. ImageNet was also used as the feature extractor in the based layer model. The global average pooling layer was added instead of the flattened layer in order to reduce the parameter size. In order to remove the overfitting of the model, the dropout layer was added. ReLU and SoftMax were used as the activation function in the hidden and entire link layers. A more detailed view of the model is given in Table 2.

Table 2. Summary of the proposed EfficientB4 architecture.

Layer (type)	Output shape	No. of parameters
Efficientnetb4 (Functional)	7×7×1792	17673823
GlobalAveragePooling2D	1792	0
dense (ReLU classifier)	256	459008
Dropout (Dropout)	256	0
dense (SoftMax classifier)	12	3084

Resnet50 is commonly used in deep learning and computer vision studies. This model was the ImageNet competition in 2015's winner. The ImageNet competition is a renowned challenge that evaluates models' ability to classify images across a large number of categories. ResNet50 is built upon a series of stacked residual units. These units enhance the model's performance by facilitating the learning process and improving the flow of gradients during training [33]. ResNet50 employs 3x3 filters, similar to the VGG16 model, and expects input images with dimensions of 224 × 224 pixels. These specifications define the size and format of the images the model can process. ResNet50 introduces the concept of skip connections, which are illustrated in Fig. 6.

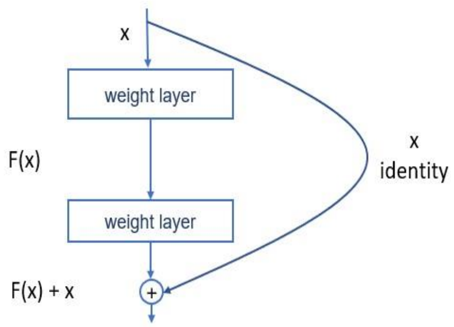

Fig. 6. ResNet skip connection.

These connections allow the gradients to flow more effectively backward during training, thereby improving the model's performance. Skip connections alleviate the problem of vanishing gradients and aid in training deeper neural networks. This paper removed the ResNet50 architecture's base model (using "include top=False"), and a new trainable layer was added. This modification allows for customizing the top layers of the ResNet50 architecture to fit the specific task or dataset at hand. The specific architecture of ResNet50, including its layers and configurations, is provided in Table 3. This table presents detailed information on the structure and parameters of the ResNet50 model used in the study.

Table 3. Summary of the proposed Resnet50 architecture.

Layer (type)	Output Shape	No. of Parameters
resnet50 (Functional)	7×7×2048	23587712
GlobalAveragePooling2D	2048	0
dense (ReLU classifier)	256	524544
Dropout (Dropout)	256	0
dense (SoftMax classifier)	12	3084

4.4. Evaluating performance using performance matrix

We described the model's performance evaluation results using four performance metrics: accuracy, precision, f1 score, and recall. These performance metrics have been used to assess the model evaluation process [34, 35] which is subdivided into 12 classes. The formulas that are used to measure the model's performance are given in Eqs. (1)-(4).

Accuracy is determined by correctly identifying and counting all occurrences across all cases. It is calculated as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

Recall determines the capability of the model to correctly identify the true positives to the total number of positive instances that were missed or not predicted.

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

Precision is a metric that assesses the accuracy of correct predictions. It is calculated by dividing the number of True positives that were correctly predicted by the total number of expected positive outcomes.

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

The F1-score refers to the harmonic mean between recall and precision. It can be assessed using this formula:

$$F1\text{-}score = \frac{Recall*Precision}{Recall+Precision} \tag{4}$$

where TP, TN, FP, and FN mean True Positive, True Negative, False Positive, and False Negative, respectively.

5. Results and Discussion

In this section, we compared the performance of the neural network architectures. MobileNetV2, EfficientNetB4, and ResNet50 and developed it using Phyton programming language based on Keras with TensorFlow as the backend. The experiments were run on a system with Intel Core i7 CPU, 2.9 GHz, X64, and 16 GB RAM. In the experimentation process of the three architectures, the dataset was divided into a train, validation, and test set, precisely 60% for training, 20% for validation, and 20% for testing the dataset. The batch size was set to 32 parameters. Adam was used as the optimization with a categorical entropy loss and a learning rate of 0.00001. The CNN models were trained for 20 epochs. Basically, the 3 CNN models have the same parameters used in the experimentation process.

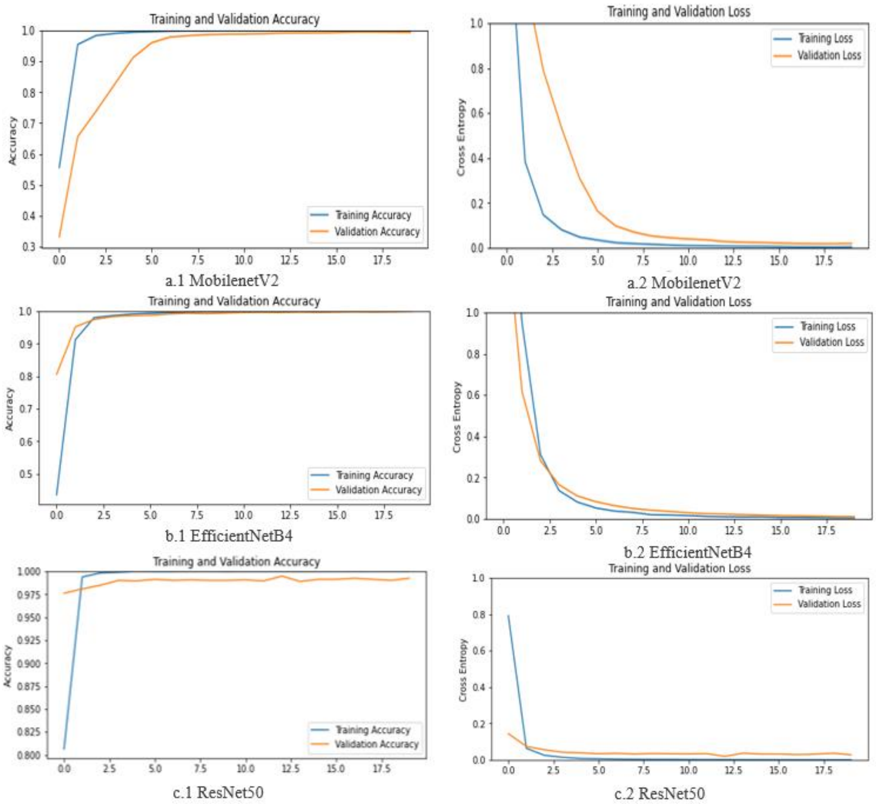

Fig. 6. Training and validation accuracy and loss using MobileNetV2, EfficientNetB4, and ResNet50.

5.1. Performance of the neural network models

MobileNetV2: Based on the 20 training steps (horizontal axis), the training accuracy values (vertical axis) are plotted as shown in Fig. 6. The figure displays that the training and validation accuracy were confined between 90% - 98% after more than five training steps. After more than five training stages, the entropy values are typically less than 0.2. It can be implied from these figures that the model 'has a higher probability of learning in the classification of bivalves using MobileNetV2.

EfficientNetB4: The model achieved an accuracy rate of 97.29% on the given task. This indicates that the model performed well in correctly classifying the input data. This model underwent 20 training steps during the experiment. The specific details and trends of the model's accuracy and loss during these processes are shown in Fig. 6. This information helps assess the model's learning progress and potential overfitting issues. Figure 6 also depicts a gradual decrease in both training and validation loss over time. This indicates that the model's predictions became more accurate as the training progressed. The final testing loss of 0.004 indicates that the model's predictions were very close to the correct predictions for the test data.

ResNet50: The training results using the ResNet50 architecture demonstrate a steady increase in accuracy over time, as visualized in Fig. 6. The final testing accuracy of 97.34% indicates that the model is performing at a very high level and is capable of making accurate predictions in the classification of marine bivalves. On the experimentation results, the training and validation accuracy of ResNet50 has increased steadily over time. The model achieves a testing loss of 0.027, which indicates that the model's predictions are close to the true values for the test data, further supporting the model's accuracy.

5.2. Comparison of the neural network model's performance

We further evaluated the metric performance results of the three architectures, as shown in Table 4. The EfficientNetB4 has the highest classification accuracy (97.29%) and followed by the ResNet50 architecture (97.16%) accuracy. The MobileNetV2 had the lowest accuracy (96.27%). The high accuracy of EfficientNetB4 architecture means that the model can extract features from images and classify them into their respective labels with correct predictions. EfficientNetB4 also achieves the highest recall rate (97.04%) than ResNet50 (97.16%) and MobileNetV2 (96.27%). However, regarding the F1-score, the EfficientNetB4 architecture achieves the highest rate (97.02%) compared to the performance of ResNet50 and MobileNetV2. F1-score is calculated by taking the average between the Recall and precision [36]. Meanwhile, the ResNet50 architecture achieved the highest rate of precision metrics (97.62%), followed by EfficientNetB4 (97.46%) and MobileNetV2 (95.20). Considering all metrics' results, the EfficientNetB4 demonstrates the most superior performance. Thus, the EfficientNetB4 model will be integrated into a mobile application that can be used to classify marine bivalves.

Table 4. Performance metric results.

Model	Accuracy	Recall	Precision	F1-score
MobileNetV2	96.27	95.90	95.90	96.02
EfficientNetB4	**97.29**	**97.04**	97.46	**97.02**
ResNet50	97.16	97.00	**97.62**	96.93

The confusion matrix was used to evaluate the performance of the mode using the EfficientNetB4 architecture. This matrix provides a tabular representation of the model's predictions compared to the actual ground truth labels.

It can be implied from the Fig. 7 that there are almost 100% correct predictions of the marine such as *Anadara granusa*, *Circe scripta*, *Codakia tigerina*, *Crassostrea iradalei*, *Gafrarium tumidum*, *Isognomon ephippium*, *Kataleysia recens*, *Lutaria philippinarum*, *Scapharca cornea a*nd *Tapes literatus*. Meanwhile, out of 160 images of *Geloina erosa* from the test set, 118 of it was correctly classified. In the images of Tellina staurella, 154 images were correctly classified, and six species were misclassified as Tapes literatus. Thus, EfficientNetB4 has correctly classified the correct species of bivalves. The model's sample images of the predicted species using EfficientNetB4 is shown on Fig. 8.

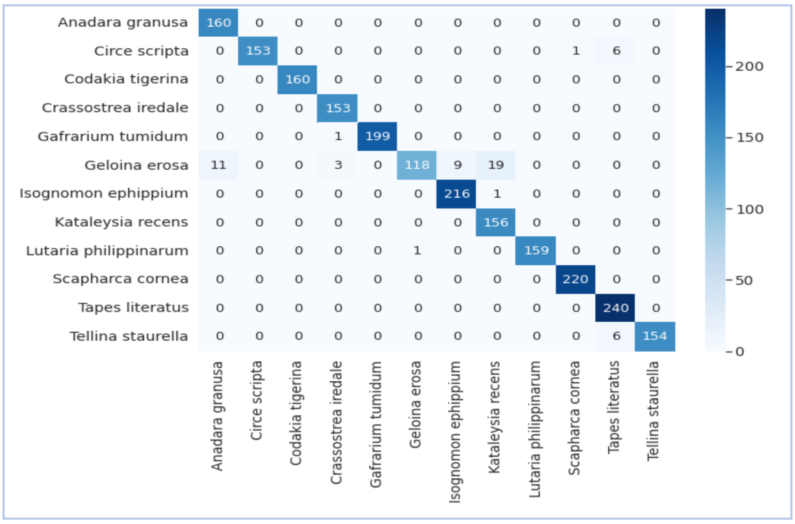

Fig. 7. Confusion matrix using EfficientNetB4 architecture.

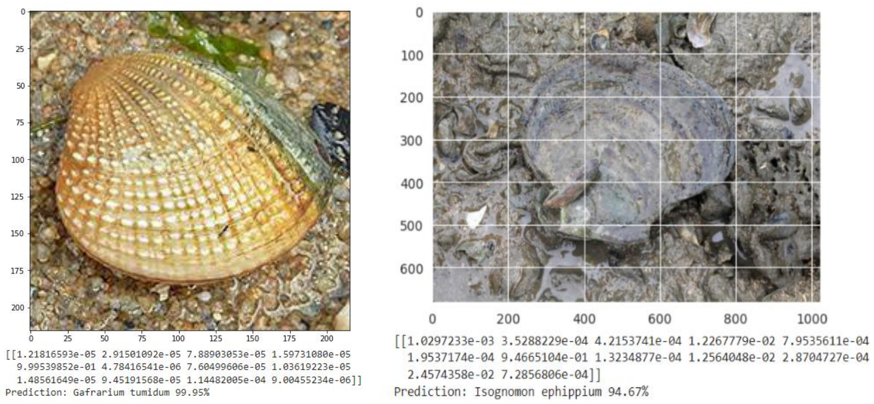

Fig. 8. Sample predicted species.

5.3. Model deployment

Lastly, we integrate the neural network model into a mobile application, as shown in Fig. 9. This application will be used as a tool to classify the bivalve species.

The mobile application was developed using Android Studio 3.1.1 and installed on a Xiaomi Mi 11 Lite mobile phone. Then the classifier model was then converted using a TF-lite converter and integrated into the mobile application. During the testing phase, various images of bivalves were captured from the coastal area to test the accuracy of the model. The model app identified the bivalves classification and provided important information such as the International Union for Conservation of Nature (IUCN) red list status and bivalve category. IUCN is an agency that provides information on the status, trends, and threats of plants and animal species.

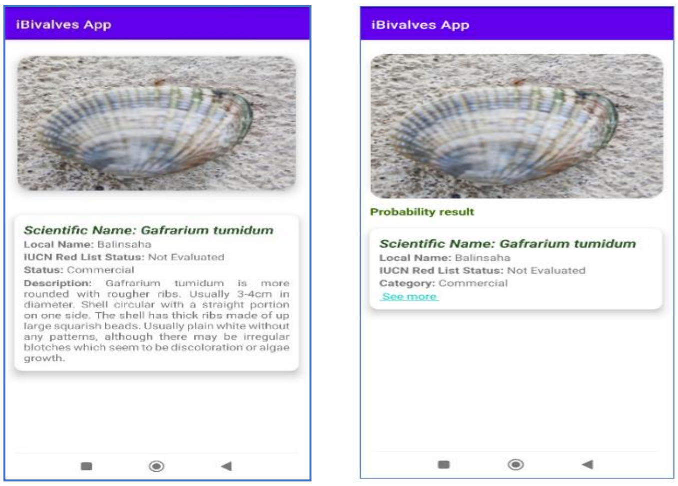

Fig. 9. Screenshot of the predicted species using the Android App.

6. Conclusions and Future Works

In this study, we focused on building the model for the classification of the bivalves species using three state-of-the-art architectures: MobileNetV2, EfficientNetB4, and ResNet50. First, various images were collected using a digital camera and smartphones from the northwestern part of Bohol, Philippines. These images served as the input in building the model.

The three neural network architectures were evaluated based on their performance metrics. The experimental results show that using the EfficientNetB4 model has significant potential in classifying marine bivalves with higher accuracy. The classification of the bivalve species is successfully developed using TensorFlow and Python. The different neural networks are trained using the images taken in the natural environment from the coastal areas.

To conclude, the modeling framework presented in this paper provided good results in image recognition. The EfficientNetB4 model is a powerful deep neural network due to its high classification accuracy and preventing the model's overfitting. Moreover, the neural network model using EfficientNetB4 was integrated into a mobile application. The installed mobile app successfully identified bivalve species from images taken in the natural environment.

In the future, we recommend adding further models in the classification of bivalves and the number of identified bivalves' classes. Lastly, we recommend a model that could classify underwater bivalves images.

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