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# Convolutional Neural Networks with MobileNetV2 Transfer Learning for Shell and Pebble Classification

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## Abstract—

In this study, we use a Convolutional neural network (CNN) strategy with the MobileNetV2 transfer learning model to classify pebbles and shells. The 4,324-image dataset was painstakingly collected and partitioned into several sets for the objectives of training, validation, and testing. The proposed Convolutional neural network (CNN) architecture was trained for 80 epochs to make effective use of MobileNetV2 for feature extraction. In addition to a notable increase in accuracy, it showed a consistent and substantial decrease in loss. The model's generalizability and resilience were further validated via testing and validation, with the results showing excellent recall and accuracy for the pebble and shell categories. Our findings demonstrate the usefulness and efficacy of transfer learning for picture classification tasks, particularly when dealing with objects having subtle visual differences, such as pebbles and shells. We achieved this by feeding MobileNetV2's pre-trained weights into the model and fine-tuning it using our dataset. Details of our proposed Convolutional Neural Network (CNN) model architecture, the steps taken to improve MobileNetV2, and experimental results demonstrating the efficacy of our approach are detailed in this article. To further prove that our method is the best at classifying pebbles and shells, we compare our results to those of other state-of-the-art approaches. The following achievements are emphasized in our paper: Constructing novel Convolutional neural network (CNN) architecture for the purpose of pebble and shell categorization. Helpful information for relevant areas of study in the future.

Keywords— Deep learning, Convolutional Neural Network, Sustainable Development, Image Classification, MobileNetV2, Pebbles, Shells.

## INTRODUCTION

In several fields, such as industrial automation, environmental monitoring, and geological investigations, image object classification plays an essential role in computer vision [1]. Two distinct but

Related natural objects, shells and pebbles, are the focus of this study's classification efforts. Pebbles and shells are common in riverbeds and coastal regions, and classifying them may tell us a lot about the geology and ecology of a place [3]. The wide variety of forms, sizes, and textures makes it challenging to distinguish between them based on appearance alone. Our recommendation for overcoming this obstacle is to use a CNN strategy that makes use of the MobileNetV2 transfer learning model [4]. When the size of the new dataset is small, transfer learning—a machine learning technique—can improve performance by adapting a model learned for one job to another comparable work [5]. Designed with mobile and embedded vision applications in mind, MobileNetV2 is a small Convolutional neural network (CNN) structure [6]. Its exceptional performance in several image classification tasks has earned it widespread reputation. Using transfer learning with MobileNetV2 to improve classification accuracy, we aim to achieve high accuracy in shell categorization. An in-depth experimental study on a real-world dataset illustrating the higher performance of our methodology in contrast to existing methodologies. You can see the overall format of the remainder of the paper here. A summary of the work pertaining to picture categorization and transfer

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learning may be found in Section 2. The technique used in our approach is detailed in Section 3, which also gives some insight into the CNN architecture and the process of fine-tuning. In Section 4, the experimental setup and findings are described, and Section 5 follows with a commentary. Section 6 concludes the report with a brief overview of our results and some recommendations for further research.

## LITERATURE REVIEW

Significant advancements have been made in several domains, including medical imaging, object identification, and understanding of natural sceneries, via the study of picture categorization using Convolutional neural networks (CNNs). The specific issue of classifying pebbles and shells, however, has received very little research. Despite the importance of Convolutional neural networks (CNNs) for natural object categorization in geological studies, environmental monitoring, and industrial applications; very little research has been published on the subject, particularly when it comes to employing transfer learning methods. Previous studies in the sector have mostly focused on similar tasks, including classifying rocks or recognizing things, but no one has paid special attention to the classification of pebbles and shells. This knowledge gap highlights the need for further study into the use of Convolutional neural networks (CNNs) and transfer learning for accurate pebble and shell classification.

## METHODOLOGY

A dataset consisting of 4,324 photographs of pebbles and shells was extracted from "Shells or Pebbles: An Image Classification Dataset." Separate sets of 2,768, 691, and 865 photos were used for training, validation, and testing, respectively, from the dataset. The Convolutional neural network (CNN) design recommended MobileNetV2 as the foundational model for TL. The design included additional layers for regularization, feature extraction, and classification, such as max pooling and dense layers, respectively. Using the training set, the model was trained for 80 iterations. At each epoch, we captured performance measures like loss and accuracy to keep tabs on the training process. Validation: To ensure the model could successfully handle fresh data, its performance was evaluated using the validation set. Noting the validation loss and accuracy at each epoch allowed us to track the model's performance over time. To find its ultimate performance, the model was evaluated using the testing set. The accuracy, precision, recall, and F1-score for both the shell and pebble classes were computed using the performance parameter table and confusion matrix. The model's ability to differentiate between pebbles and shells was tested after the confusion matrix and performance parameters were examined. Conclusions and possible improvement areas were explored using the analysis's findings. Part A: The Dataset We used is "Shells or Pebbles: An Image Classification Dataset," and it has 4,324 photos in all. Figure 1 shows the classification of the dataset into three parts: training, validation, and testing. Each set has a different number of images: 2,768, 691, and 865, respectively. There was a distribution

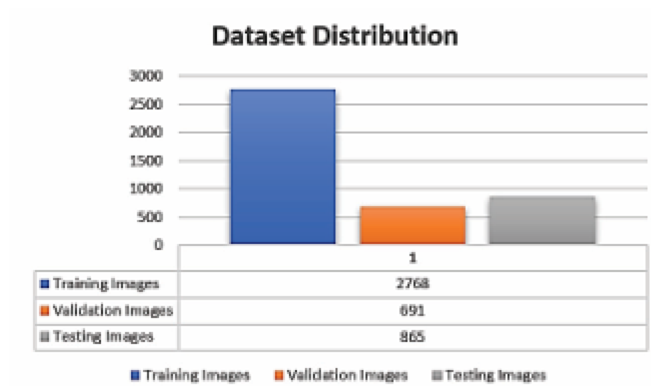


Fig. 1. Distribution of Dataset


Fig. 2. Input Dataset

Been chosen to provide a sufficient amount of pictures for CNN model training and a distinct subset

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for validation to adjust hyper parameters and prevent over fitting. In order to evaluate the model's efficacy on fresh data, the testing set was kept apart. The dataset is comprehensive and challenging for our picture classification challenge since it covers a broad variety of photographs exhibiting varied forms, sizes, and textures of pebbles and shells. The pictures or dataset used to train the suggested model is shown in Figure 2. Section B: Convolutional Neural Network Architecture

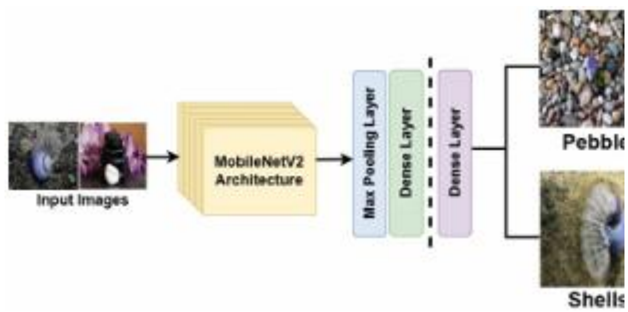


Fig. 3. Proposed CNN Model

By the use of the MobileNetV2 Transfer Learning Model to classify shells and pebbles, the suggested CNN architecture makes use of MobileNetV2 transfer learning. It has several important layers: The feature extraction model that is built upon is MobileNetV2. Figure 3 shows the subsequent layers: a max pooling layer, a dense layer, a regularization dropout layer, and finally, a dense layer for the final classification. The design makes use of MobileNetV2's powerful feature extraction capabilities, tailoring the last layers to suit the specific characteristics of pebble and shell photos.

TABLE I. PROPOSED CNNARCHITECTURE WITH MOBILENETV2 TRANSFER LEARNING MODEL

| Layers | Input shape | Output shape | Number of filters | Parameters |
|---|---|---|---|---|
| MobileNetV2 | 5,5,1280 | 5,5,1280 | 1280 | 2257984 |
| Max pooling2d_1 | - | - | - | 0 |
| Dense | - | - | - | 244859 |
| Dropout_ | - | - | - | 0 |
| Dense_1 | - | - | - | 198 |
| Total Parameters: 2,503,041<br>Trainable Parameters: 245,057<br>Non-Trainable Parameters: 2,77,935 | | | | |

The Convolutional neural network (CNN) architecture that uses MobileNetV2 transfer learning to categorize pebbles and shells is shown in Table 1. Each of the architecture's many levels has its own unique set of input and output formats, filters, and configuration options. First, the transfer learning model that is utilized most often is MobileNetV2. It takes in data in the form of 5x5x1280 and returns data in the same format. With 1,280 filters and 2,257,984 parameters, this context isn't suitable for training. 2. A max pooling operation is performed by the Max Pooling2D_1 layer. Nevertheless, the supplied table is missing details about the input/output geometries, filter counts, and parameters. Thirdly, dense: this layer is an entirely connected one with parameters, filter numbers, and input/output formats that are not specified. 4. Although it does not provide details, the Dropout layer does apply dropout regularization. 5. Dense_1: yet another fully connected layer whose specs are not specified. The proposed architecture inherits 2,503,041 non-trainable parameters from the MobileNetV2 base model and 245,057 trainable parameters. To categorize pebbles and shells, this architecture uses the pre-trained MobileNetV2 model to extract features and then tweaks the last layers to be more specialized. Consequently, there is a severe lack of trainable parameters. III. Outcomes the study delves into the several factors that were taken into account during the inquiry. Using the Mobile Net Transfer Learning Model [9] and the Adam optimizer [7, 8], the research trained a Convolutional Neural Network (CNN) model as proposed. With a batch size of 32, the training procedure included 80 epochs [10]. The Results section presents the results from each epoch in a tabular manner, with accompanying graphical representations showing the model's accuracy, validation loss, validation accuracy, and losses overall. Here we go into further depth on the

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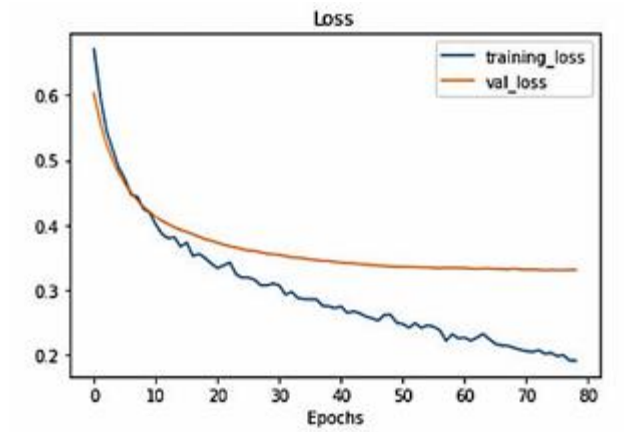
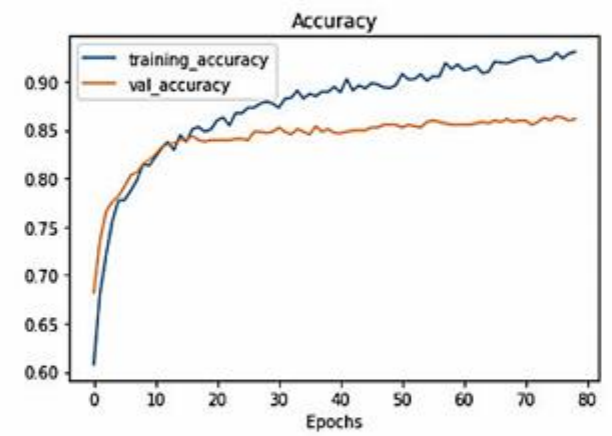
features of the Confusion Matrix. More than that, we break it all down and explain everything in depth. In addition to the model's predictions, the conclusion includes the following metrics: accuracy, precision, recall, and F1-score. In the Results section, the findings are presented in a structured and detailed manner. A. Evaluation according to Epoch performance traits the metrics for the CNN model's performance at various training epochs using MobileNetV2 transfer learning are shown in Table 2. Each column represents a different metric: epoch, training accuracy, validation accuracy, validation loss, and training loss. Declining loss values and increasing accuracy demonstrate that the model's performance improves as training progresses over epochs. With a training accuracy of 93.16% and a loss of just 0.1906 at epoch 80, the model is rather good. With an accuracy rate of 86.11% and a loss of 0.3306, the validation process is complete. You can learn a lot about the model's performance in terms of these indicators.

| Epoch | Loss | Accuracy | Validation Loss | Validation Accuracy |
|---|---|---|---|---|
| 1 .. | 0.6706 .. | 0.6077 .. | 0.6027 .. | 0.6816 .. |
| 10 .. | 0.4191 .. | 0.8132 .. | 0.4203 .. | 0.8191 .. |
| 20 .. | 0.3401 .. | 0.8504 .. | 0.3755 .. | 0.8394 .. |
| 30 .. | 0.3096 .. | 0.8772 .. | 0.3546 .. | 0.8480 .. |
| 40 .. | 0.2716 .. | 0.8945 .. | 0.3427 .. | 0.8466 .. |
| 50 .. | 0.2491 .. | 0.8963 .. | 0.3357 .. | 0.8553 .. |
| 60 .. | 0.2249 .. | 0.9176 .. | 0.3336 .. | 0.8553 .. |
| 70 .. | 0.2073 .. | 0.9241 .. | 0.3312 .. | 0.8596 .. |
| 80 | 0.1906 | 0.9306 | 0.3306 | 0.8611 |

Figure 4 depicts the performance of the CNN model using MobileNetV2 transfer learning

Training and validation phases totaling more than 80 iterations. As the training loss steadily drops from 0.6706 to 0.1906, it becomes clear that the model is doing a great job of absorbing the information it needs to function. Also, the training accuracy goes up from 0.6077 to 0.9306, which means the model can




The accuracy of the training picture classification improves. As the validation accuracy rises from 0.6816 to 0.8611 and the validation loss falls from 0.6027 to 0.3306, a corresponding trend emerges. As seen by the improvement in validation performance throughout training, the findings show that the model has high data generalization. B. Research using the Confusion matrix's properties Figure 6 shows the confusion matrix, which analyzes the CNN model's classification results for pebbles and shells using MobileNetV2 transfer learning. The predicted and real picture labels divide the matrix into four equal halves. With 486 pebbles and 269 shells properly identified, the diagonal components of the matrix indicate the count of correctly recognized photos. The out-of-diagonal parts represent mistakes in categorization; for example, 40 pebbles were wrongly thought to be shells and 70 shells were wrongly thought to be pebbles. Overall, the confusion matrix provides valuable information about the model's performance, specifically pinpointing its strengths and areas that need improvement in terms of

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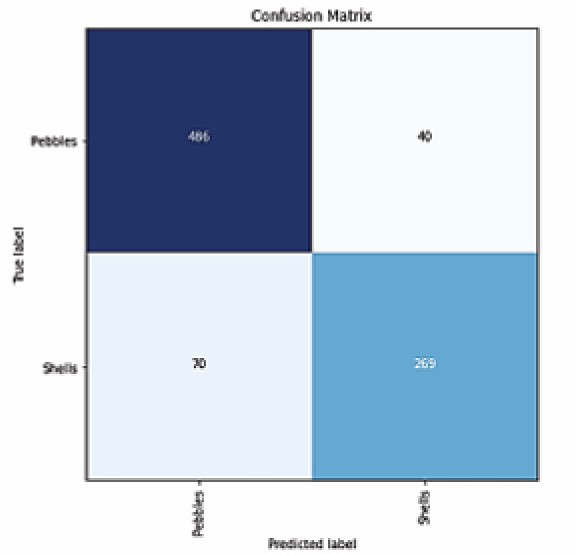
consistently distinguishing between pebbles and shells.




Criteria for Classification The accuracy, precision, recall, and F1-score for the shell and pebble classification using the CNN model with MobileNetV2 transfer learning are shown in Table 3. One measure of accuracy is precision, which is defined as the percentage of positive predictions (pebbles or shells) that really occurred relative to the total number of positive predictions. The proportion of correctly predicted positive occurrences relative to the overall number of real positive occurrences is measured by recall, also known as sensitivity. One statistical metric that finds the harmonic mean of recall and accuracy is the F1-score. A fair assessment of these two indicators may be achieved with its help. The percentage of cases that are correctly categorized relative to the total number of instances is called accuracy. With 0.87 precision, 0.92 recall, 0.90 F1-score, and 0.87 accuracy, the model was able to classify stones. For shells, the model achieved a recall of 0.79, an F1-score of 0.83, and a precision of 0.87. These measures show that the model does a good job of classifying pebbles, but it does a little worse job of classifying shells, since the F1-score and recall are lower for shells than for pebbles.

TABLE III. PERFORMANCE PARAMETER

| Name of the class | Precision | Recall | F1-Score | Accura |
|---|---|---|---|---|
| Pebbles | 0.87 | 0.92 | 0.90 | 0.87 |
| Shells | 0.87 | 0.79 | 0.83 | |

## CONCLUSION

Our findings demonstrate that the MobileNetV2 model can effectively employ transfer learning to distinguish between pebbles and shells. The CNN architecture proved its adaptability and learning capacity after training over many epochs by steadily improving performance measures. Both classes' excellent recall and accuracy show that the model can distinguish between these real-world items. The significance of transfer learning and its efficacy in contexts with sparse data is highlighted in this research. To make the model more accurate and useful in real-world scenarios, further study might look at various data augmentation approaches and fine-tune it.

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