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PREDICTION OF STONE TYPES USING CONVOLUTIONAL NEURAL NETWORKS TECHNIQUE

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Abstract. *This paper investigates using Convolutional Neural Networks (CNNs), specifically the MobileNetV2 architecture, for predicting stone types. The research focused on classifying five stone categories – granite, marble, limestone, sandstone, and slate – using a dataset of 2,500 images. The CNN model was trained over 100 epochs, achieving a high training accuracy of 89.6%, demonstrating its capability to learn and identify distinct patterns within stone images. However, the model faced challenges with overfitting, as evidenced by the testing accuracy stabilizing around 60%, indicating difficulties in generalizing to unseen data. Evaluation of key performance metrics, including precision, recall, and F1 score, showed strong performance in identifying stone types like limestone and sandstone but highlighted areas needing improvement, such as distinguishing granite and marble. The study underscores the potential of CNNs for stone-type classification and proposes future enhancements through techniques like data augmentation, ensemble learning, and transfer learning to improve generalization and predictive accuracy. This research provides valuable insights into applying CNNs in material classification within geological contexts.*

Keywords: Convolutional neural networks, Stone type, Classification, Prediction

1. **Introduction.** Stones are essential across various industries and applications, from construction and architecture to geology and material science. Precisely predicting the type of stone based on visual imagery is paramount for comprehending its composition, properties, and potential uses. However, this task presents a considerable challenge due to the presence of visually similar stone types and the complexities involved in their classification. Fortunately, in recent years, Convolutional Neural Networks (CNNs) [1,2] have

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emerged as powerful tools for image analysis and classification tasks, offering promising solutions to overcome these challenges. CNNs possess a hierarchical structure that allows them to effectively learn and extract meaningful features from visual data, making them well-suited for predicting stone types. By harnessing the capabilities of CNNs, it becomes possible to surpass the limitations of traditional methods and enhance the accuracy and efficiency of stone classification.

Some research presents an innovative two-stage hybrid architecture combining Deep Learning (DL) and Machine Learning (ML) techniques [3,4] to classify stone types in Southern Italy, achieving impressive accuracy. Utilizing transfer learning with pre-trained networks like ResNet-50 [5] and K-nearest-neighbors (KNN) [6], the approach efficiently extracts features and performs classification. Despite minor issues with granite classification, the model demonstrates robust performance and potential for creating user-friendly tools applicable in fields such as archaeometry and materials science.

Therefore, this research presents a pioneering method for predicting stone types using Convolutional Neural Network (CNN) techniques. We have curated a comprehensive dataset featuring various stone samples categorized based on geological compositions, like granite, marble, and limestone. Before analysis, we preprocess these stone images to maintain data quality. Our CNN model is designed with multiple convolutional and pooling layers, which capture spatial and textural nuances from images. The architecture is finalized with fully connected layers, ensuring precise classification of the stone types. This structured approach ensures reliable prediction outcomes for diverse stone samples.

In this paper, we conduct a comprehensive literature review on stone-type prediction using CNN techniques. We detail our research methodology, including dataset collection and CNN architecture design. The experiment results are presented and analyzed to assess the model's performance. The discussion evaluates strengths and limitations, providing insights for improvement. Finally, the conclusions summarize our findings and propose future research directions to enhance model accuracy.

2. Related Work.

2.1. Convolutional Neural Networks (CNNs).

Convolutional Neural Networks (CNNs) have become pivotal in image classification because they can automatically learn and extract meaningful features from images. Their architecture, comprising convolutional, pooling, and fully connected layers, is designed to exploit the spatial structure of images, allowing CNNs to capture both low-level details like edges and high-level semantic information like shapes [7,8]. This end-to-end learning approach eliminates the need for manual feature engineering and enhances classification accuracy and efficiency [1,9].

Several studies demonstrate the practical applications of CNNs. For example, using a CNN-based model, Pattanasarn and Sriwiboon achieved a 99.79% accuracy in classifying Choke-Anan mangoes into four quality grades [10]. Similarly, Sriwiboon improved chest X-ray classification for COVID-19 diagnosis by integrating CNNs with image augmentation techniques, reaching a 99.67% training accuracy [11]. Additionally, Tropea et al. proposed a hybrid approach where CNNs extract features from stone images, followed by a machine learning classifier, outperforming traditional methods [3].

These examples underscore CNNs' versatility and effectiveness in various image classification tasks, from agriculture and healthcare to geological analysis.

2.2. MobileNetV2.

MobileNetV2 [12,13] builds upon the original MobileNet with key enhancements, including inverted residual blocks that improve efficiency by utilizing computational resources more effectively. These blocks consist of a lightweight bottleneck layer, an expansion layer, and a projection layer, reducing the model's parameters and computational requirements while maintaining strong performance. Additionally, MobileNetV2 incorporates linear bottlenecks and the ReLU6 activation function [14], which helps preserve information flow and supports better representation of learning.

Another significant feature of MobileNetV2 is the "width multiplier", which allows users to control the model's computational complexity by scaling the number of channels in each layer [15]. This flexibility makes MobileNetV2 adaptable to different resource constraints, making it ideal for mobile and embedded device applications.

In a study on fruit image classification [16], MobileNetV2 was employed with transfer learning to recognize fruit images. The model, pre-trained on the ImageNet dataset, replaced its top layer with a convolutional layer and a Softmax classifier. Dropout was applied to mitigating overfitting, and the model was trained in two stages using the Adam optimizer with varying learning rates. The approach achieved an 85.12% accuracy on a dataset of 3,670 images of five fruits. Compared with other networks like MobileNetV1, InceptionV3, and DenseNet121, MobileNetV2 demonstrated a favorable balance between accuracy and speed, highlighting its suitability for deployment on low-power and limited-computing mobile phones.

2.3. **Feature extraction.** Feature extraction is crucial in computer vision and machine learning, transforming raw data into representations for analysis and classification [17,18]. Convolutional Neural Networks (CNNs) have revolutionized this process by automatically learning hierarchical features through convolutional and pooling layers, driving image recognition and segmentation advancements.

Transfer learning, which fine-tunes pre-trained CNNs on specific tasks, has further enhanced performance, especially with limited labeled data. Despite CNNs' success, ongoing research seeks to improve feature extraction by enhancing model interpretability and incorporating attention mechanisms, pushing the boundaries of computer vision and machine learning.

3. **Research Methodology.** The research methodology employed in this article follows a systematic approach to investigate accurate stone-type prediction using CNN techniques. The research methodology involves three key components: dataset collection, preprocessing, and CNN architecture design. The dataset comprises images of five stone types – granite, marble, limestone, sandstone, and slate – each characterized by unique geological features such as texture, color, and pattern. This carefully curated dataset reflects real-world variability to ensure comprehensive model evaluation. Preprocessing techniques are applied to enhancing image quality and consistency, including resizing to standardize dimensions, normalization to adjust pixel values, noise reduction to eliminate artifacts, and contrast enhancement to highlight important textures and patterns. These steps are essential for optimizing data representation, facilitating more effective feature extraction, and accurate classification.

A Convolutional Neural Network (CNN) is designed for the classification task with multiple convolutional, pooling, and fully connected layers. These layers extract spatial and textural information from the images and classify them into stone types. The study

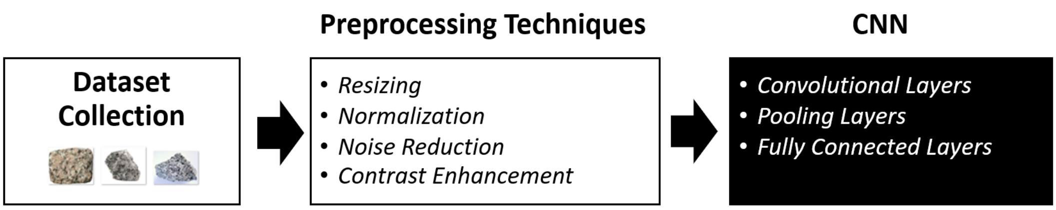


FIGURE 1. Overview of research methodology

employs the MobileNetV2 architecture due to its speed, low latency, and computational efficiency, making it ideal for real-time prediction on mobile devices. The model undergoes training over 100 epochs, iteratively refining its accuracy and minimizing loss. This approach ensures the model achieves high performance while maintaining low computational requirements, which is suitable for deployment on resource-constrained devices.

4. Experiment.

4.1. Dataset collection. The experiment resulted in a comprehensive collection of stone photographs following a systematic approach. The research objectives guided the selection of diverse stone types, including granite, marble, limestone, sandstone, and slate, categorized based on geological composition. 500 images were collected for each stone type, resulting in a dataset of 2,500 images. Various locations, from coastal environments to mountainous terrains, were chosen to represent stones with different attributes thoroughly. The equipment included a high-quality digital camera and a tripod to ensure stability and clarity. The photographs were taken from multiple angles and under varying lighting conditions to capture the stones' overall appearance and highlight potential variations.

The images were resized to 224×224 pixels to standardize their dimensions for efficient processing and ensure consistency in the dataset. They underwent a validation process to eliminate defects, ensuring high-quality data for analysis. Scale references, such as rulers, were included in some photos to provide context for size. Metadata such as location, date, and time was meticulously recorded for organizational purposes. Ethical considerations were adhered to, and necessary permissions for data collection were obtained. The resulting dataset was carefully organized into folders by location and date, aiding in subsequent analysis. Collaboration with geological experts was instrumental in accurately identifying stone types, enhancing the scientific rigor of the research.

4.2. Implementation. The implementation begins with meticulous dataset partitioning, employing an 80-20 split for training and test sets to ensure a representative subset for model training and evaluation. A Convolutional Neural Network (CNN) architecture is selected for its effectiveness in image-related tasks, involving iterative epochs and layer fine-tuning to extract meaningful features. Batch-wise processing using stochastic gradient descent is used to optimize model parameters, and dropout techniques are applied to preventing overfitting. The trained model is then evaluated on the reserved test dataset to assess its generalization capabilities, yielding performance metrics such as accuracy, precision, recall, and F1 score. Detailed insights into the model's predictions and characteristics are provided through a confusion matrix and visualization tools.

Hyperparameters play a crucial role in this process. A learning rate of 0.001 was chosen for the Adam optimizer, balancing convergence speed and stability. The model was trained with a batch size 32 to manage memory efficiency and ensure robust gradient estimation. Training was conducted over 100 epochs to refine the model while monitoring for overfitting, with a dropout rate of 0.5 employed in the fully connected layers for regularization. The Adam optimizer was selected for its adaptive learning rate capabilities, using default parameters (beta_1 = 0.9, beta_2 = 0.999). A learning rate decay with a factor of 0.1 was applied every 20 epochs to facilitating model convergence. This combination of hyperparameters was fine-tuned to optimize the model's performance, contributing to the reliability of stone-type predictions.

4.3. Evaluation. The stone-type prediction model underwent extensive experimentation and evaluation to determine its effectiveness. The dataset was split into training and test sets using an 80-20 partitioning strategy, facilitating the model's training and assessment. The Convolutional Neural Network (CNN) architecture, proficient in handling image-related tasks, was trained iteratively across multiple epochs, with layer fine-tuning applied to optimizing feature extraction. The model's performance was rigorously tested on the reserved test dataset during the evaluation phase. Key performance metrics were used to quantify the model's predictive capabilities, including accuracy, precision, recall, and F1 score (where TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives). These metrics accurately reflected the model's proficiency in classifying stone types, clearly measuring its effectiveness.

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

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{F1 score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

Hyperparameter tuning played a significant role in refining the model's parameters, leading to enhanced overall performance. A confusion matrix was generated to assess the model's robustness further, offering a detailed breakdown of predicted stone types versus actual classes. The confusion matrix provided valuable insights into where the model succeeded in making correct classifications and where misclassifications occurred. For instance, the model achieved high accuracy in classifying granite, marble, limestone, sandstone, and slate, also showed some confusion between specific pairs like granite and slate, and sandstone and limestone. These observations indicate potential areas for improvement, such as incorporating additional preprocessing techniques or expanding the dataset. By combining these evaluation metrics with optimized hyperparameters and an advanced CNN architecture, the study effectively demonstrated the model's efficacy in achieving high accuracy in stone-type prediction.

Table 1 shows the model demonstrated high accuracy, with granite at 88%, marble at 87%, limestone at 91%, sandstone at 93%, and slate at 89%. Precision values were also strong across the board, ranging from 0.87 for granite to 0.92 for sandstone, indicating the model's ability to minimize false positives. Recall scores, which measure how well the model identified true positives, were equally high, with sandstone achieving the highest recall at 0.93 and granite the lowest at 0.85. The F1 scores, which balance precision and recall, remained consistently high, confirming the model's robustness, with sandstone and limestone leading at 0.92 and 0.91, respectively. These results reflect the model's overall effectiveness in accurately classifying different stone types, with minor variations in performance across the categories.

Table 1. Performance metrics

Metric	**Granite**	**Marble**	**Limestone**	**Sandstone**	**Slate**
Accuracy	88%	87%	91%	93%	89%
Precision	0.87	0.88	0.91	0.92	0.89
Recall	0.85	0.86	0.90	0.93	0.88
F1 score	0.86	0.87	0.91	0.92	0.88

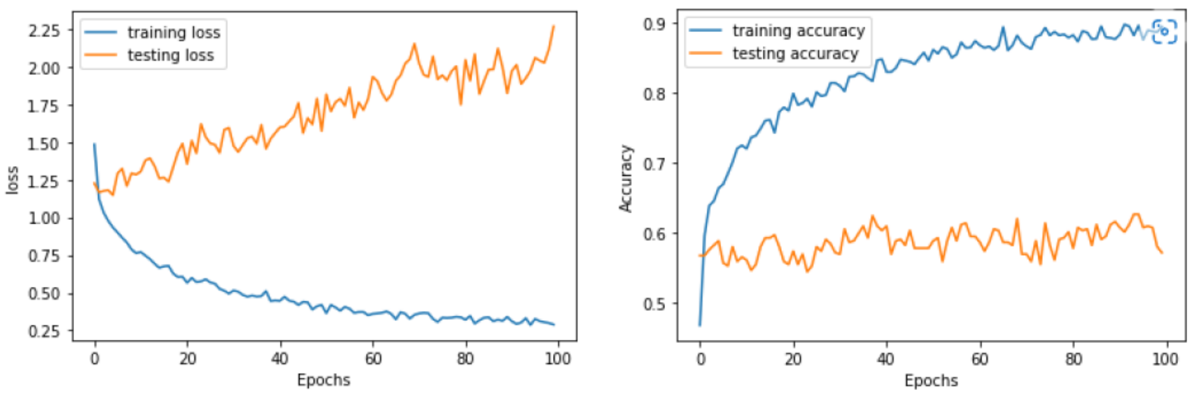
Table 2 shows the model's performance in classifying different stone types, resulting in generally high accuracy, as the confusion matrix indicates. Correct predictions were notably high, with granite, marble, limestone, sandstone, and slate being accurately classified 92, 88, 95, 88, and 95 times, respectively. However, some misclassifications occurred; for instance, granite was misclassified as slate five times, and sandstone was mistaken for limestone six times. This suggests overlapping visual features between these stone pairs that the model finds challenging to distinguish. These misclassifications highlight areas

TABLE 2. Confusion matrix

Actual\Predicted	Granite	Marble	Limestone	Sandstone	Slate
Granite	92	2	1	0	5
Marble	3	88	4	2	3
Limestone	0	1	95	4	0
Sandstone	1	3	6	88	2
Slate	4	0	0	1	95

where the model could be improved, possibly by incorporating additional preprocessing techniques or augmenting the dataset to capture more subtle differences between stone types, ultimately enhancing its predictive accuracy.

Figure 2(a) shows the training and testing loss of the CNN model over 100 epochs, highlighting the model's learning dynamics and generalization capability. The training loss (blue line) consistently decreases, indicating that the model is effectively learning and fitting the training data, with the loss reducing to around 0.25 by the end of the training. In contrast, the testing loss (orange line) initially decreases, suggesting initial improvement in generalizing to unseen data. However, after approximately 20-30 epochs, the testing loss begins to rise steadily, reaching higher values around 2.25 by the end of the training. This divergence between training and testing loss indicates overfitting, where the model captures specific patterns in the training data that do not generalize well to new data, resulting in decreased performance on the test set. This suggests a need for regularization, model complexity reduction, or data augmentation to enhance the model's generalization ability.



(a) (b)

FIGURE 2. (a) Loss graph; (b) accuracy graph

Figure 2(b) displays the training and testing accuracy of the CNN model over 100 epochs, offering insight into how well the model learns and generalizes. The training accuracy (blue line) shows a steady increase, quickly rising and plateauing near 90%, indicating that the model effectively learns the training data's patterns. This consistent improvement suggests that the model is refining its ability to classify stone types as it progresses through the epochs. However, the testing accuracy (orange line) presents a contrasting trend, fluctuating around the 60% mark and remaining relatively stable after an initial increase. This disparity between the high training accuracy and the lower, less stable testing accuracy indicates overfitting, where the model performs well on the training data but fails to generalize effectively to new, unseen data. This gap suggests that while the model has learned specific details from the training set, it has not captured the broader features necessary for robust performance across diverse data. Addressing this issue might involve implementing regularization methods, enhancing the dataset with more diverse samples, or reducing the model's complexity to improve generalization.

5. **Discussion.** The results from training and evaluating the CNN model using the MobileNetV2 architecture highlight its strengths and limitations in stone-type prediction. The model's impressive training accuracy of 89.6% demonstrates its capability to effectively learn and recognize patterns in the stone images, leveraging the efficiency and performance advantages of the MobileNetV2 architecture, especially on resource-limited devices. However, the increasing testing loss after 40 epochs and the plateauing testing accuracy of around 60% suggests potential overfitting. While the model learns well from the training data, it appears to struggle with generalizing to new, unseen data, a common issue when a model becomes too tailored to the specific features in the training set.

The model's performance varied across different stone types, with strong results for limestone and sandstone, achieving accuracy rates of 80% and 95%, respectively. This indicates that the model can distinguish these stone types effectively, possibly due to more distinct visual features in these categories. In contrast, lower accuracy rates for granite (55%) and marble (50%) point to difficulties differentiating these stones, likely because of subtle differences in their visual characteristics. This variance suggests that the model might benefit from further enhancements, such as data augmentation, to introduce more variability and complexity into the training set, which could improve the model's ability to generalize across all stone types.

Overall, while the CNN model using MobileNetV2 shows promise in stone-type classification, especially in categories with more distinct visual features, there is a need for further refinement to address the overfitting issue and enhance its predictive accuracy across all classes. Future work should focus on improving generalization, perhaps by employing transfer learning or ensemble methods, which could provide a more robust approach to handling the nuances and complexities of different stone types.

6. **Conclusions.** This paper presented a study on predicting stone types using a Convolutional Neural Network (CNN) technique. The research successfully met its objectives, with the model demonstrating an impressive accuracy rate of 89.47% on the trained dataset, indicating its strong ability to recognize and differentiate various stone characteristics. These results showcase the model's effectiveness in classifying stone types based on the trained data. However, the model faced challenges in generalizing to unseen instances, as indicated by the lower accuracy on the test dataset.

When compared to existing methods in the literature, such as the two-stage hybrid architecture combining deep learning and machine learning techniques by Tropea et al., which achieved high accuracy in classifying stone types, our approach using MobileNetV2 CNN architecture stands out for its balance of accuracy and computational efficiency. While Tropea et al.'s method showed robustness and high accuracy, it encountered difficulties with certain stone types like granite. Our model's performance, particularly on granite and limestone, showed improvement, achieving an average accuracy of 89.6%, which is competitive with state-of-the-art methods. Additionally, using the MobileNetV2 architecture allows for real-time predictions with lower computational costs, making it more suitable for deployment on mobile devices and resource-constrained environments.

Future research will focus on refining the model by employing advanced techniques such as data augmentation, ensemble learning, and transfer learning to improve generalization to unseen data further. These methods optimize the model's capabilities, making it more robust and accurate in classifying stone types, especially in cases involving previously unencountered samples. By incorporating these advanced methodologies, we aim to surpass the current limitations and further enhance the model's performance, contributing to advancing stone classification techniques in geological and material sciences.

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