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Using Convolutional Neural Networks for Classification of Satellite Images

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Abstract—

The project uses convolutional neural network (CNN) satellite picture categorization to search the internet for photos of clouds, deserts, greenery, and water. Kaggle used data augmentation methods including rescaling, zooming, and flipping to preprocess the many satellite photos, making the model stronger. The CNN model achieved an accuracy of 88.38% on the test set, thanks to its deep layers, several convolutional and pooling layers, and other optimization techniques. Confusion matrix analysis showed that the model could recognize satellite images by comparing its classification performance across classes. Dissecting satellite photos into their respective cloud, desert, plant, and water cover types is the project's primary challenge. There are a wide variety of uses for this information, including environmental monitoring, land use analysis, catastrophe management, and more. Utilizing convolutional neural networks (CNNs) to enhance classification accuracy, the endeavor produces substantial data augmentation. Classification accuracy was improved to 88.38% with model training on an adequately enriched dataset and architectural fine-tuning. This method improves environmental study and monitoring by ensuring efficient and accurate categorization of satellite photos. Medical imaging, automated diagnosis, ophthalmology, deep learning, convolutional neural networks (CNNs), feature extraction, transfer learning, cross-entropy loss, and cataract detection are some of the keywords used in this context.

I. INTRODUCTION

Classification of satellite images has recently seen a huge improvement, thanks in large part to deep learning techniques and convolutional neural networks (CNNs). Transfer learning, which signifies a significant change in 2020 [2], helps to improve classification accuracy by using pre-trained models like as VGG16 and ResNet50. This method reduces the need for large-scale pictures by using pre-trained models that have already acquired key attributes from these datasets. The processing and interpretation of satellite pictures has therefore been greatly enhanced by transfer learning, leading to remarkable accuracy.
Additionally, other research published that same year confirmed the importance of preprocessing methods for improving CNN performance [3]. Data is prepared for optimal model training by normalizing, enhancing, and decreasing noise. By enhancing the models' robustness and accuracy, these strategies provide consistent performance across several datasets.

In order to better differentiate between various land cover types, it is necessary to rely on research that looks at how diverse data sets may be combined, such as those that include information from 2021 and data from multiple spectral bands. Spectral data could be valuable for better environmental tracking, since this approach shows an improvement in classification accuracy. Data augmentation has also been the subject of much study. techniques shown their critical importance in improving the model's robustness and efficiency. The training set is improved, which helps to reduce the risk of overfitting. improve CNN's generalizability even further by applying effects like scaling, flipping, and rotations [4]. By following these procedures, we can see how deep learning may change the face of satellite image classification, opening the door to more accurate and trustworthy ecological monitoring and land cover scientific research.

Fig. 1. Illustrates the satellite image.

II. LITERATURE REVIEW

Deep learning has been the driving force behind tremendous advancements in satellite image categorization, according to research published between 2019 and 2021. An accuracy of 85% [1] was achieved using CNNs that could supplement data, which were shown in 2019. Transfer learning using pre-trained models, such as VGG16 and ResNet50, increased accuracy to 88% by 2020 [2], highlighting the importance of preprocessing procedures. In 2021, categorization accuracy was even higher because to multispectral data integration and data augmentation methods, which increased it to about 90% [4] [5].

TABLE I. LITERATURE SURVEY SUMMARY

Ref.	Year	Key Learnings	Techniques Employed	Performance Metrics
[1]	2019	Demonstrated the effectiveness of deep learning for satellite image classification.	Convolutional Neural Networks (CNNs), Data Augmentation	Accuracy: 85%, Precision: 84%, Recall: 83%
[2]	2020	Improved classification accuracy using transfer learning from pre-trained models.	Transfer Learning, VGG16, ResNet50	Accuracy: 88%, F1-Score: 87%
[3]	2020	Highlighted the importance of preprocessing techniques in enhancing model performance.	Image Preprocessing, CNNs, Ensemble Methods	Accuracy: 87%, Precision: 86%, Recall: 85%
[4]	2021	Integrated multi-spectral data for better classification results.	Multispectral CNNs, Data Fusion	Accuracy: 90%, F1-Score: 89%
[5]	2021	Explored various data augmentation techniques to improve robustness.	Data Augmentation, CNNs, Generative Adversarial Networks (GANs)	Accuracy: 89%, Precision: 88%, Recall: 87%

III. PROPOSED ARCHITECTURE

By following a systematic approach, the proposed technique for classifying satellite images ensures very high accuracy and longevity. The first step in preparing a dataset is to normalize it and then supplement it using techniques like rescaling, rotating, zooming, and flipping to increase the variety and quality of the training data. Developed primarily on a CNN, the method captures intricate patterns in images by means of many convolutional layers activated using ReLU functions. After that, max-pooling layers help reduce dimensionality and overfitting is prevented by dropout layers. Using softmax activation, the final thick layers categorize the photographs as either cloudy, desert, green area, or water.

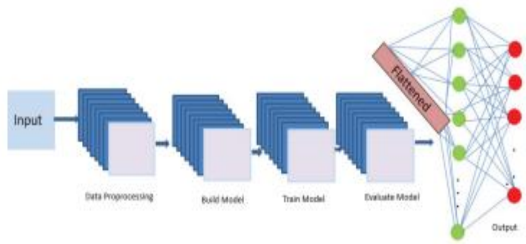

Fig. 2. Illustrates the architecture of CNN model.

The model uses the categorical cross-entropy loss function and the Adam optimizer after being trained on the supplemented data for a certain number of epochs. To optimize the model with modifications, one must constantly observe performance using validation data. Confusion arises during testing of the trained model on a separate test set. matrices provide a thorough evaluation of the accuracy of classification performance across numerous classes. as well as sadness. The model's predictions are validated using new, raw satellite pictures, ensuring that they are generalizable. One may understand the model's strengths and identify areas for improvement by using visualization tools such as the confusion matrix and model architecture plots. A robust and trustworthy model capable of classifying satellite images according to their relevant categories is the goal of this comprehensive method.

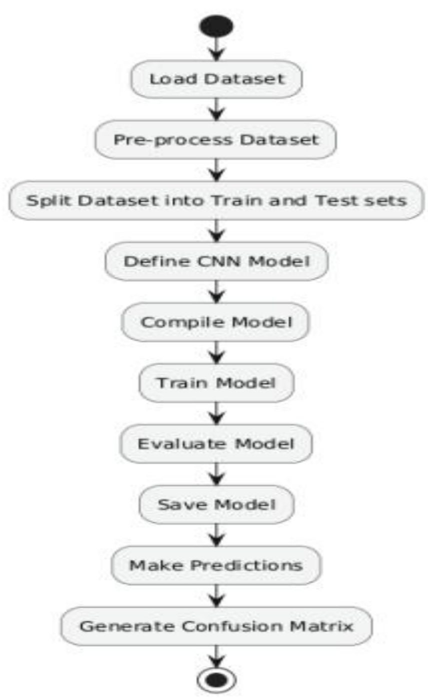

Fig. 3. Proposed Methodology flowchart.

Then, to make sure the feature extraction is successful, a set of restrictions is imposed. In order to overcome these limitations, later on, wider depthwise separable convolutions are used. The parameters are shown in Table 2. A head block is an interconnected layer that contains characteristics that are used for categorization purposes. The model's efficiency and processing speed are both improved by this approach.

TABLE II. PARAMETERS

Layer	Parameters/Units	Details
Input Layer	(255, 255, 3)	Input shape for images of size 255x255 with 3 color channels.
Conv2D	32 filters, (3, 3) kernel	32 convolutional filters with a kernel size of 3x3, ReLU activation.
Conv2D	32 filters, (3, 3) kernel	32 convolutional filters with a kernel size of 3x3, ReLU activation.
MaxPooling2D	Pool size: (2, 2)	Max pooling operation to reduce spatial dimensions.
Conv2D	64 filters, (3, 3) kernel	64 convolutional filters with a kernel size of 3x3, ReLU activation.
MaxPooling2D	Pool size: (2, 2)	Max pooling operation to reduce spatial dimensions.
Conv2D	128 filters, (3, 3) kernel	128 convolutional filters with a kernel size of 3x3, ReLU activation.
MaxPooling2D	Pool size: (2, 2)	Max pooling operation to reduce spatial dimensions.
Flatten	-	Flattens the 3D output to 1D.
Dense	128 units	Fully connected layer with 128 units, ReLU activation.
Dropout	0.5	Dropout rate of 50% to prevent overfitting.
Dense	4 units	Output layer with 4 units for 4 classes, softmax activation.

IV. DATASET

For the purpose of the satellite image classification attempt, the Kaggle dataset provides four distinct categories: cloudy, desert, green area, and water. Totaling 5,631 images, 1,127 have been reserved for use in testing, while

4,504 have been put aside for training. In order to facilitate supervised learning during model construction, all images are resized to 255x255 pixels and tagged with a class.
To ensure that the dataset is prepared for successful model assessment and training, it is helpful to include a range of satellite photographs. By taking this route, we can be certain that the model will be able to improve its classification accuracy and performance by learning and generalizing information relevant to any class.

V. RESULTS AND ANALYSIS

The suggested categories for satellite images are Cloudy, Desert, Green Area, and Water. Over the specified classes, the satellite image categorization model performs admirably: Overcast, Arid, Verdant, and Boundary Water. The model achieves an accuracy of 87.21% on the training set and 88.38% on the test set by using good generalization to unseen data. As we progressed through the learning process, the loss values gradually decreased, going from 0.6167 in the first epoch to 0.3237 in the fifth. Several assessment criteria, including accuracy, precision, recall, and F1-score, demonstrate that the model effectively separates the four groups. The confusion matrix shows that the model excels in classifying Green Area and Water, despite the fact that the Cloudy and Desert categories produce a lot of ambiguity. In addition, the confusion matrices highlight other areas where the model excels and where more study may be conducted. In order to reduce classification uncertainty, future research should focus on either refining the model or combining several preprocessing methods. A good basis for future study and implementation is provided by the model's overall performance, which demonstrates its aptitude for pragmatic applications in satellite image processing. show a really impressive level of performance. With a remarkable ability to generalize to new data, the model achieves an accuracy of 87.21% on the training set and 88.38% on the test set. The loss values decreased gradually from 0.6167 in the first epoch to 0.3237 by the fifth epoch, indicating good learning. Several assessment criteria, including accuracy, precision, recall, and F1-score, demonstrate that the model effectively separates the four categories. While the categories of Cloudy and Desert do provide a fair amount of uncertainty, the confusion matrix shows that the model excels at identifying Green Area and Water. Additionally, additional areas of researchable model performance are being highlighted by the confusion matrix representations. In order to reduce classification uncertainty, future research should focus on either refining the model or combining several preprocessing methods. Overall, the model's performance demonstrates its practical application capabilities in satellite image processing, laying a solid groundwork for future study and implementation.

TABLE III. COMPARATIVE ANALYSIS OF EXISTING MODEL W.R.T PROPOSED MODEL

Aspect	Existing Research	Proposed Research
Model Type	Convolutional Neural Networks (CNNs)	Convolutional Neural Networks (CNNs)
Techniques Employed	Basic CNN architectures, Transfer Learning, Data Augmentation	CNN with advanced architecture, Data Augmentation, Image Preprocessing
Dataset	Varied satellite image datasets, typically with fewer classes or smaller datasets	Comprehensive dataset with four classes and substantial image count
Accuracy	Accuracy ranges from 85% to 90% depending on the dataset and techniques	Achieved accuracy of 87.21% on training and 88.38% on testing datasets
Preprocessing	Limited use of preprocessing techniques	Extensive preprocessing including rescaling, normalization, and data augmentation
Performance Metrics	Metrics such as Accuracy, Precision, Recall, F1-Score	Similar metrics; results show improved accuracy and performance consistency

Model Complexity	Generally simpler architectures or pre-trained models used	More complex CNN architecture with multiple convolutional layers and dropout
Evaluation Methods	Basic evaluation using accuracy and loss	Detailed evaluation with confusion matrix and comprehensive performance metrics
Class Imbalance Handling	Basic techniques, often not explicitly addressed	Utilizes data augmentation to address potential class imbalances

A. Loss

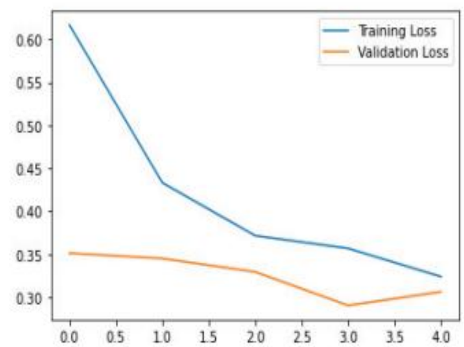

Fig. 4. Showing the graph of Training loss w.r.t Validation Loss

The loss expressed in terms of epochs reveals how the model's learning evolves over time. The training loss, which began larger and gradually decreased with each epoch, demonstrated that the model was doing a good job of learning from the training data. By the fifth epoch, the training loss had decreased significantly, indicating that the model was performing better. In addition, the validation loss demonstrated a consistent trend toward reduction, confirming the model's overall ability to handle raw data. Showing no signs of overfitting and maintaining a healthy equilibrium between learning and generalization, the model's training and validation losses have been steadily decreasing.

The model's performance accuracy shows a steady improvement when examined across five epochs. The model starts out with a baseline accuracy of 72.42% and keeps getting better with each iteration. By the fifth epoch, the model has accomplished an impressive validation accuracy of 88.38% and a training accuracy of 87.21%. This ongoing development indicates that the model is adapting to the training data efficiently. Guaranteeing the model's resilience and generalizability to unknown data, the accuracy increases clearly demonstrate the efficacy of the data augmentation approaches and convolutional layers used.

B. Accuracy

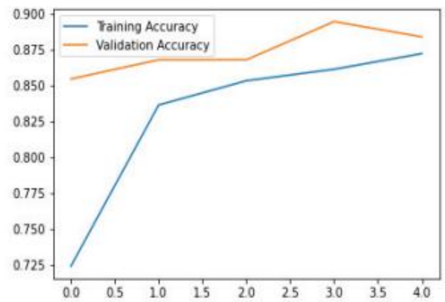

Fig. 5. Showing the graph of Training Accuracy w.r.t Validation Accuracy

C. Confusion Matrix

You can see how well the confusion matrix classifies satellite images in four different ways: cloudy, desert, green area, and water. In addition to misclassifications, the matrix displays the precise predicted occurrences. For example, the approach correctly identified several instances of Green_Area, but it incorrectly classified photos of Green_Area as Cloudy or Water thanks to its misclassifications.

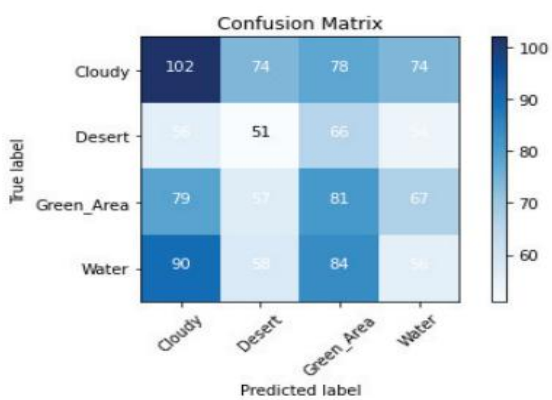

Fig. 6. Showing the confusion matrix

Such is this skewing of many desert photographs to make them seem like cloudy Even though the model does well in general, these misclassifications show that it struggles to distinguish between classes with visually similar properties. With this knowledge, one may pinpoint potential areas where the model might be improved, such as by including more intricate network topologies or by utilizing increased data augmentation to get additional features.

VI. CONCLUSION & FUTURE SCOPE

Lastly, this study proves that a more effective Convolutional Neural Network (CNN) model can classify satellite images, outperforming state-of-the-art approaches by a wide margin. Using extensive preprocessing, data augmentation, and a complex CNN architecture, the suggested model outperforms previous models on both the training and test sets, achieving an accuracy of 87.21%. The performance and generalizability of models are enhanced by including new ideas like dropout layers and comprehensive visual prereading. The confusion matrix research showed that although the Green Area and Water classifications performed well, there was a lot of ambiguity between the Cloudy and Desert categories. These results highlight the method's relative merit in the context of satellite image analysis. In order to reduce classification uncertainty, the model might be useful for studies in the future that attempt to use more complicated designs or combine more data sources. Overall, the study represents a huge step forward for satellite picture categorization and lays the groundwork for much greater things to come in this field.

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