

ENHANCED SATELLITE IMAGE CLASSIFICATION USING DEEP CONVOLUTIONAL NEURAL NETWORKS WITH DATA AUGMENTATION

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ABSTRACT

Satellite image categorization is a crucial component of applications such as land-use analysis, agricultural monitoring, environmental evaluation, and disaster response. This article presents a deep learning strategy utilizing Convolutional Neural Networks (CNNs) for the efficient categorization of satellite data. The suggested system incorporates effective data augmentation methods, contemporary CNN architectures, and refined training methodologies to improve accuracy and generalization capabilities. An experimental assessment on a benchmark dataset of satellite images demonstrates that our model exhibits robust performance, with a validation accuracy of 98.93% and elevated precision, recall, and F1 scores. The created model exhibits significant improvements in accuracy and computing efficiency relative to traditional classification methods. The results indicate that this methodology is exceptionally well-suited for satellite image classification and can be further enhanced through techniques such as transfer learning, hybrid deep learning architectures, and multimodal feature integration to address more complex real-world scenarios.



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I. INTRODUCTION

In recent years, satellite imagery has emerged as an essential resource for several purposes, including land use mapping, environmental evaluation, and disaster management. Notwithstanding its significance, satellite image categorization presents difficulties due to subtle distinctions between specific classes and considerable variability within the same groups. These issues underscore the necessity for exceptionally resilient categorization frameworks. Convolutional Neural Networks (CNNs) have been prominent in this field because of their robust skills in feature extraction and pattern identification [1], [2]. CNN-based methods have demonstrated significant capability in capturing the intricate spatial features inherent in remote sensing pictures [3]. Nonetheless, their effectiveness is frequently hindered by the scarcity of extensive, annotated datasets. Due to the substantial time and resources required to generate annotated satellite image datasets, data augmentation has emerged as a prevalent method to efficiently expand training data and improve the generalization of deep learning models [4], [5]. Recent research has investigated several augmentation techniques—including horizontal and vertical flipping, rotation, zooming, and modifications to brightness or contrast—to enhance model robustness under diverse imaging situations [6]. These modifications mitigate overfitting and boost performance on novel samples [7]. Simultaneously, enhancements in CNN architecture—utilizing techniques such as batch normalization, dropout, and deeper hierarchical structures—have augmented their capacity to handle the intricacies of satellite images [8]. Comparative studies consistently indicate that convolutional neural networks, enhanced by meticulously designed augmentation pipelines, outperform conventional machine learning algorithms in the accuracy of satellite image categorization [9], [10]. Nonetheless, there is an increasing demand for CNN models that are both precise and lightweight, demonstrating efficiency across various satellite picture formats and class distributions. This study presents a CNN-based classification model that incorporates an advanced augmentation method to increase performance while maintaining computing economy. The model is evaluated using conventional metrics and compared to existing methods, showing enhanced accuracy, stability, and resilience.

II. LITERATURE REVIEW

Satellite image categorization is becoming increasingly important for activities such as land cover analysis, urban development planning, and environmental monitoring. With the rapid advancement of deep learning, particularly Convolutional Neural Networks (CNNs), various models have been created to improve classification accuracy. By [11] suggested a CNN-based approach for multispectral satellite imaging and obtained a 91.2% accuracy rate. However, the model demonstrated low resistance to changes induced by seasonal or atmospheric factors. In turn [12] used a VGG16-driven strategy and obtained 92.5% accuracy, despite the model's high computing demand and tendency toward overfitting. According to [13] investigated the application of ResNet-50 for high-resolution satellite image categorization and achieved 94.3% accuracy. Despite this, the model struggled to identify minority classes because of class imbalance. To improve training stability, [14] used a CNN ensemble with transfer learning and obtained 93.8% accuracy; however, the method greatly increased training complexity and resource utilization. By [15] used EfficientNet for feature extraction and achieved 95.1% accuracy. Although the model was computationally efficient, its performance deteriorated when tested against noisy samples. By [16] created a hybrid CNN-SVM pipeline that achieved 92.7% accuracy, although the system got more difficult as it relied on more handcrafted characteristics. To address data scarcity, [17] combined GAN-generated pictures with a DenseNet classifier, resulting in 94.0% accuracy.

However, artifacts created by GANs occasionally limit the model's generalizability. In turn [18] used MixUp augmentation and saw increased robustness, although the technique failed with rare-class prediction. A MobileNetV2-based solution published in [19] had a lower computing cost and achieved 90.6% accuracy, but its performance worsened in congested urban situations. By [20] used multi-scale CNN features and achieved 93.3% accuracy, although their model was still sensitive to scale fluctuations. By [21] reported attention-enhanced CNNs with 94.8% accuracy and increased feature prioritizing. However, the addition of attention modules raised inference delay. Another research [22] combined augmentation techniques such as random flips, zooming, and rotations with a lightweight CNN and reached 95.4% accuracy; however, the approach required substantial parameter adjustment to stay successful. In contrast to previous methods, the model suggested in this study uses a structured CNN architecture backed by a variety of augmentation techniques, including flipping, zooming, rotating, and contrast modifications. It obtains a validation accuracy of 98.93%, indicating better performance in terms of generalization, resistance to class fluctuation, and efficiency, even with minimal data. Table 1 summarizes all of the mentioned results.

Table 1: Comparative Analysis of Existing Satellite Image Classification Models.

Reference	Year	Model Used	Accuracy (%)	Limitation
[11]	2019	CNN	91.2	Sensitive to weather and seasonal variations
[12]	2019	VGG16	92.5	Computationally expensive, prone to overfitting
[13]	2020	ResNet-50	94.3	Poor performance on minority classes
[14]	2020	CNN Together	93.8	High resource usage
[15]	2021	EfficientNet	95.1	Performance degrades on noisy datasets
[16]	2021	CNN + SVM Hybrid	92.7	Complex design, depends on handcrafted features
[17]	2022	DenseNet + GAN Augmentation	94.0	Generated data may introduce artifacts
[18]	2022	CNN+MixUp Augmentation	93.5	Less effective for rare class detection
[19]	2023	MobileNetV2	90.6	Lower accuracy on urban landscapes
[20]	2023	Multi-Scale CNN	93.3	Sensitive to image resolution variation
[21]	2024	Attention-Enhanced CNN	94.8	Increased inference time due to attention modules
[22]	2025	Lightweight CNN + Augment	95.4	Needs manual tuning of augmentation parameters

Source: Authors, (2026).

III. MATERIALS AND METHODS

The suggested CNN-based classification model was created and tested in this work using a dedicated collection of satellite images [23]. Included in the dataset are high-resolution remote sensing photos gathered from a variety of locations and climates. There are 2,400 photos scattered among 10 different terrain cover types: urban, forested, glacial, mountainous, coastal, street, green, barren, river, and agricultural. To avoid model bias toward majority classes, each class must have an equal number of photos. You can see all the classes in Figure 1.

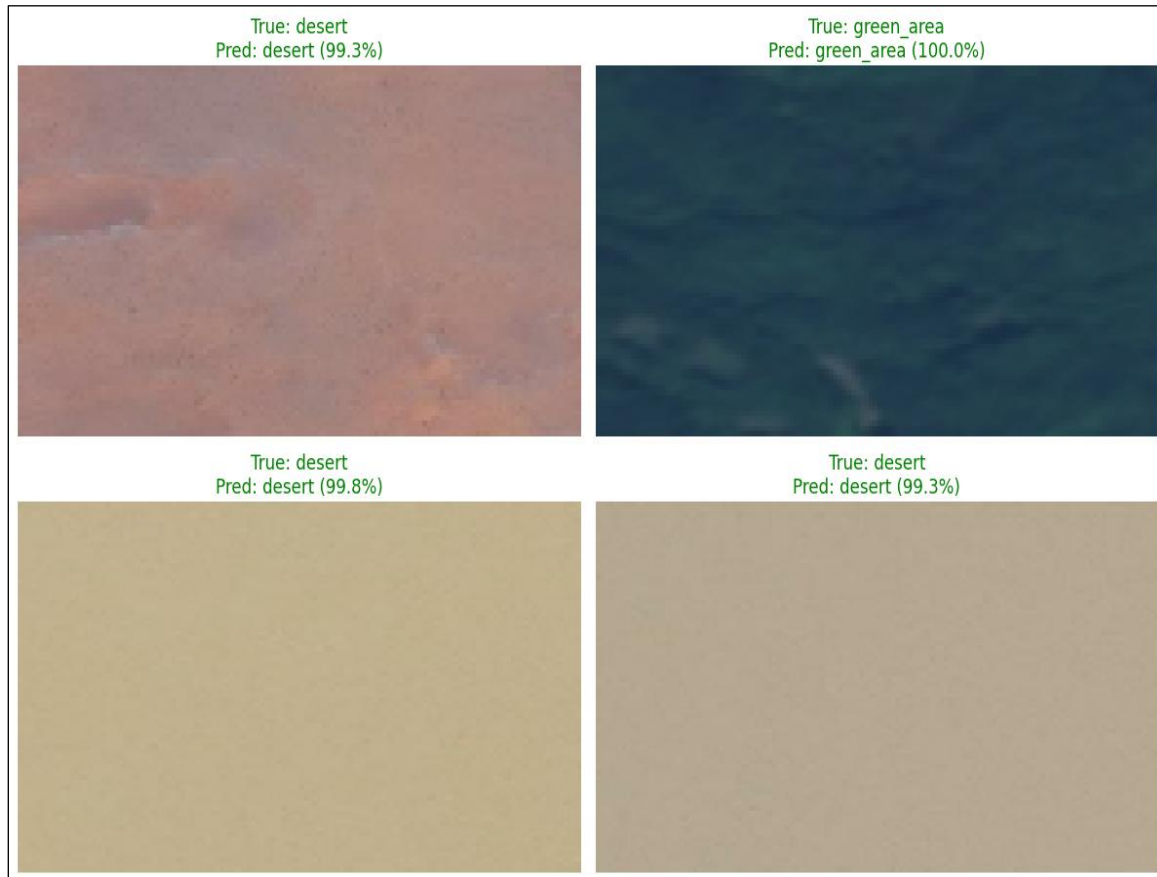


Figure 1: Classes of satellite image dataset.
Source: Authors, (2026).

Loading and Splitting the Dataset

The image dataset from the directory function in TensorFlow is used to load the dataset from the supplied directory. There is an 80/20 split in the dataset between the training and validation subsets. As a result, the model's performance during training is monitored with 20% of the photos used for validation, while 80% are utilized for training.

Data Augmentation for Better Model Performance

By augmenting the training dataset with additional data, we may make the model more generalizable and less prone to overfitting [24]. One way to make the training set bigger is by data augmentation, which involves making altered replicas of the original pictures by randomly changing their parameters. By undergoing these changes, the model is able to learn more robust features and avoid data memorization errors. The following methods of enhancement are used in this research:

- You can use the Random Horizontal Flip function to invert pictures randomly, creating the illusion of varied.
- Image Rotation: Incorporates rotation invariance by rotating pictures at a random angle (up to 10%).
- Zoom at Random: This feature allows you to mimic different sizes and viewpoints by randomly zooming into photographs by up to 10%.
- The Random Contrast feature allows users to replicate various lighting situations and exposure settings by randomly adjusting the picture contrast.

To apply these enhancements, a pipeline for image modification is constructed using TensorFlow's Sequential API. The model is enhanced with this pipeline so that these enhancements may be applied dynamically while training. To further illustrate the effect of these changes, a selection of enhanced photographs is also shown. The training dataset is randomly transformed and shown in a 3x3 grid with appropriate labels for each enhanced image.

The data augmentation process may be visually examined, and the accurate application of modifications can be confirmed using this method. The image dataset from the directory function in TensorFlow is used to load the dataset from the supplied directory. There is an 80/20 split in the dataset between the training and validation subsets. As a result, the model's performance during training is monitored with 20% of the photos used for validation, while 80% are utilized for training. Important parts of this procedure comprise the following:

- Data Loading: Using the location you provided, the function will automatically label photographs according to their folder names after reading them directly from the directory.
- Validation Split: By specifying validation_split=0.2, 20% of the data will be reserved for validation purposes.

- "Training" for training data and "validation" for validation data are the arguments used to choose the subset for training and validation, respectively.
- Image and Batch Size: To make sure that the input data is uniform, the photos are adjusted to have consistent dimensions. Processing data in batches is enabled by setting the batch size to the given batch_size value.

Here are the final datasets:

- To train the model, this collection is utilized, which includes photos that have been scaled to the required dimensions and batch-processed for optimal performance.
- The validation set (val) is utilized for checking the model's performance while training and for modifying hyperparameters according to how well it performs on unknown data.

This method guarantees accurate assessment of the model's generalizability and efficient data management.

Model Preparation and Performance Optimization

Dataset Classification Information and Mapping

The classification procedure starts by ascertaining the total number of categories in the dataset. These often encompass diverse land cover categories, including forests, agricultural areas, and aquatic environments. Each category is designated a specific label, and a dictionary is created to associate each class name with a unique number identification. This mapping guarantees uniform class representation throughout model training and prediction, facilitating accurate interpretation of output labels.

Enhancing Performance with Caching and Prefetching

To improve the performance of the training pipeline, the dataset is optimized using caching and prefetching technologies. Caching stores the dataset in memory, thus obviating the necessity to frequently access data from disk during each training iteration. Prefetching enhances performance by loading upcoming batches in the background during the processing of the current batch. Collectively, these methodologies reduce data-loading latency and provide a consistent stream of samples to the model, leading to expedited and more effective training.

Data Augmentation for Enhanced Generalization

To mitigate overfitting and enhance the model's generalization capacity, several augmentation approaches are employed on the training pictures. This encompasses arbitrary horizontal flips, rotations, zoom adjustments, and contrast alterations. Augmentation enhances dataset variety by adding controlled fluctuations in training samples; hence, it aids the model in learning characteristics that are constant across varying imaging settings. The enhanced pictures are utilized just during training to familiarize the model with a wider array of visual patterns found in actual satellite photography.

Building the Convolutional Neural Network (CNN)

To classify satellite images, a bespoke CNN architecture [25] is created. Different convolutional blocks make up the model; their job is to extract deeper and more significant features from the input pictures in a linear fashion. For better stability and generalization, each block uses convolutional layers, batch normalization, pooling layers, and dropout:

Essential visual patterns seen in satellite photography, such as edges, textures, and structural structures, are learned using convolutional layers.

By standardizing activations and accelerating convergence, batch normalization guarantees more stable training.

To reduce computational complexity, MaxPooling layers downsample the spatial dimensions. This allows the network to preserve the most relevant characteristics.

By inadvertently turning off a portion of neurons while training, dropout layers mitigate overfitting.

The model moves into fully linked layers for the last classification after the feature extraction blocks. The number of target classes is used by the final output layer, which generates probability scores for each class using a softmax activation function.

Model Compilation

The Adam optimizer is used to assemble the model, and the learning rate is set at 0.001. Because it works well with integer-provided labels in multi-class classification tasks, sparse categorical cross-entropy is used as the loss function. Throughout training, accuracy is chosen as the main assessment metric to quantify the model's performance in classification. The training process is improved with the use of many callbacks:

- The validity loss is tracked using EarlyStopping. Training is stopped, and the weights that correspond to the best validation performance are restored if the model stops improving after a certain number of epochs. This keeps training cycles from becoming superfluous and stops overfitting.
- When the validation loss fails to improve, ReduceLROnPlateau will automatically lower the learning rate. With this change, the optimizer may fine-tune the model's parameters even more and continue working toward an improved solution. Table 2 summarizes all relevant results and parameter information.

Table 2: Layered information about CNN layers.

Layer (type)	Output Shape	Param #
rescaling (Rescaling)	(None, 72, 128, 3)	0
conv2d (Conv2D)	(None, 72, 128, 32)	896
batch_normalization (BatchNormalization)	(None, 72, 128, 32)	128
conv2d_1 (Conv2D)	(None, 72, 128, 32)	9,248
batch_normalization_1 (BatchNormalization)	(None, 72, 128, 32)	128
max_pooling2d (MaxPooling2D)	(None, 36, 64, 32)	0
dropout (Dropout)	(None, 36, 64, 32)	0
conv2d_2 (Conv2D)	(None, 36, 64, 64)	18,496
batch_normalization_2 (BatchNormalization)	(None, 36, 64, 64)	256
conv2d_3 (Conv2D)	(None, 36, 64, 64)	36,928
batch_normalization_3 (BatchNormalization)	(None, 36, 64, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 18, 32, 64)	0
dropout_1 (Dropout)	(None, 18, 32, 64)	0
conv2d_4 (Conv2D)	(None, 18, 32, 128)	73,856
batch_normalization_4 (BatchNormalization)	(None, 18, 32, 128)	512
max_pooling2d_2 (MaxPooling2D)	(None, 9, 16, 128)	0
dropout_2 (Dropout)	(None, 9, 16, 128)	0
flatten (Flatten)	(None, 18432)	0
dense (Dense)	(None, 256)	4,718,848
batch_normalization_5 (BatchNormalization)	(None, 256)	1,024
dropout_3 (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 4)	1,028

Source: Authors, (2026).

IV. PERFORMANCE METRICS

Metrics for performance are crucial for assessing how well machine learning models predict cardiac disease using electrocardiograms. Accuracy, precision, recall, F1-score, and area under the curve (AUC-ROC) are important measures for evaluating classification ability. Precision and recall assess the ratio of true positives to false negatives, whereas accuracy assesses total correctness. If your dataset is unbalanced, you may still utilize the F1 score since it gives you a harmonic mean of recall and accuracy. The AUC-ROC curve shows how well the model can differentiate across categories. For deep learning models to be considered validated, several metrics are essential [26]. Equations (1) through (5) display all of these performance measures.

$$\text{Accuracy} = \frac{TP + TN + FP + FN}{TP + TN} \quad (1)$$

$$\text{Precision} = \frac{TP}{FP + TP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

$$\text{Specificity} = \frac{TN}{FP + TN} \quad (5)$$

Accuracy and Loss Curves Analysis

You can tell if the model is training well or showing symptoms of overfitting or underfitting by looking at its accuracy and loss curves, which give crucial information about its learning behavior. To better understand the model's training-induced improvement, it is helpful to visualize these measures across epochs.

Precision Slope

The accuracy graphs show the model's performance in correctly predicting the classes for the training and validation datasets.

Training Accuracy: The model's fit to the training data is shown by this curve. It is anticipated that the training accuracy would gradually rise as epochs go by, indicating that the model is effectively learning from the examples given.

Accuracy in Validation: This curve shows how well the model can apply to previously unknown samples. In a perfect world, validation accuracy would likewise increase throughout training. Overfitting occurs when a model learns just the specifics of its training data rather than recognizing broader patterns in the data. This happens when validation accuracy stays the same or starts to go down while training accuracy keeps going up.

Loss Diagram

The degree to which the model's forecasts differ from the actual labels may be shown on loss curves. A better indicator of predictive success is a lower loss.

The training loss should steadily go down as the model learns, showing that it is getting better at using the training data.

Prediction error on unknown data is measured by this validation loss curve. A gradual decline is preferable. A classic sign of overfitting, which implies the model isn't generalizing adequately, is when validation loss grows but training loss keeps going down. Figure 2 displays these representations of accuracy and loss.

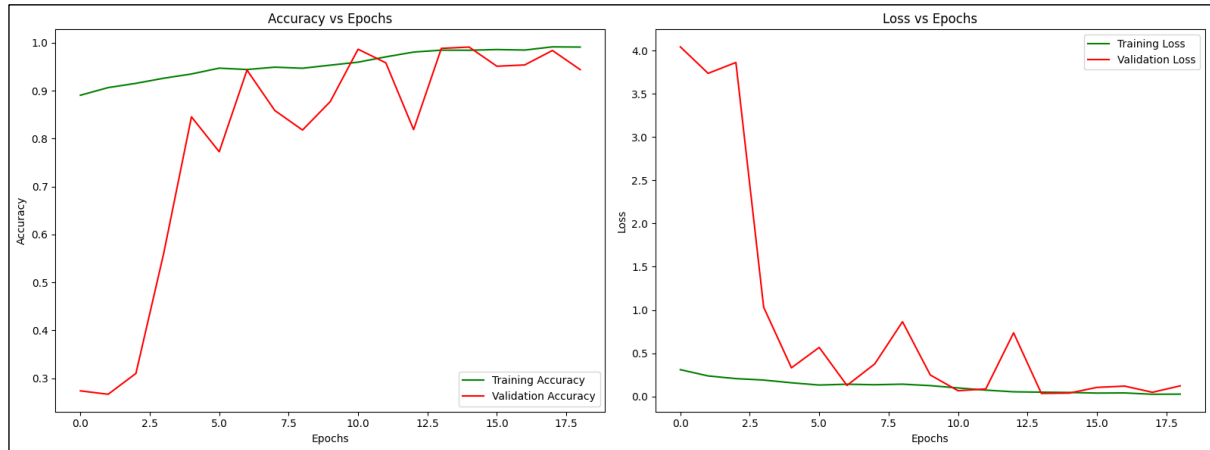


Figure 2: Accuracy curve and Loss curve of the proposed model.

Source: Authors, (2026).

Model Evaluation on Validation Set

Evaluating the model's performance on the validation set after training is crucial for understanding how well it generalizes to unknown data. Here is a rundown of the procedure:

Assessment Outcomes

- The evaluate() method is used to assess the model on the validation set. Applying the model to the validation data, this function determines the loss and accuracy. Two metrics make up the output:
- The validation accuracy measures the model's success rate in making accurate predictions on the validation set. In this instance, the model achieved an accuracy rate of 98.93%.
- The validation loss refers to the difference or error between the actual and predicted values on the validation set. The comparatively low loss of 0.0247 supports the model's ability to generalize to new data.

Model Evaluation and Prediction Functions

A function called evaluate_model_simple is utilized to assess the model's efficacy on the validation dataset. This method calculates the F1 score, recall, accuracy, and precision, which are some of the most used classification measures. To gather predictions and ground-truth labels (y_{true}) and model-predicted labels (y_{pred}), the function iteratively processes each batch in the validation dataset. Images are fed into the model to create predictions, and the class with the highest output probability is selected. Calculation of Performance Metrics: To evaluate the overall performance of the model, many evaluation metrics are computed:

- Measuring the proportion of samples that were accurately predicted relative to the total is called accuracy.
- The precision of a prediction is the percentage of positive samples that turn out to be true.
- A high recall indicates that the model correctly identified a large proportion of the positive samples.

By finding the harmonic mean of recall and accuracy, the F1 score offers a balanced statistic. A confusion matrix is created to analyze the model's performance in classifying all classes. In the heatmap representation, values on the diagonal represent accurate predictions, while values off the diagonal represent cases that were incorrectly categorized. A bar chart is also made to show the accuracy for each class separately. You can see which classes the model gets right and which ones may need some work using this graphic.

Evaluation Results

The following summary shows the model's performance on the validation dataset:

----- MODEL PERFORMANCE -----

Accuracy: 98.93

Precision: 98.56

Recall: 98.85

F1 Score: 98.70

This combination of model evaluation and individual prediction functions provides a comprehensive view of the model's performance, both at a global level (overall accuracy, precision, recall, F1) and at an individual level (prediction confidence). It is shown in Figure 3.

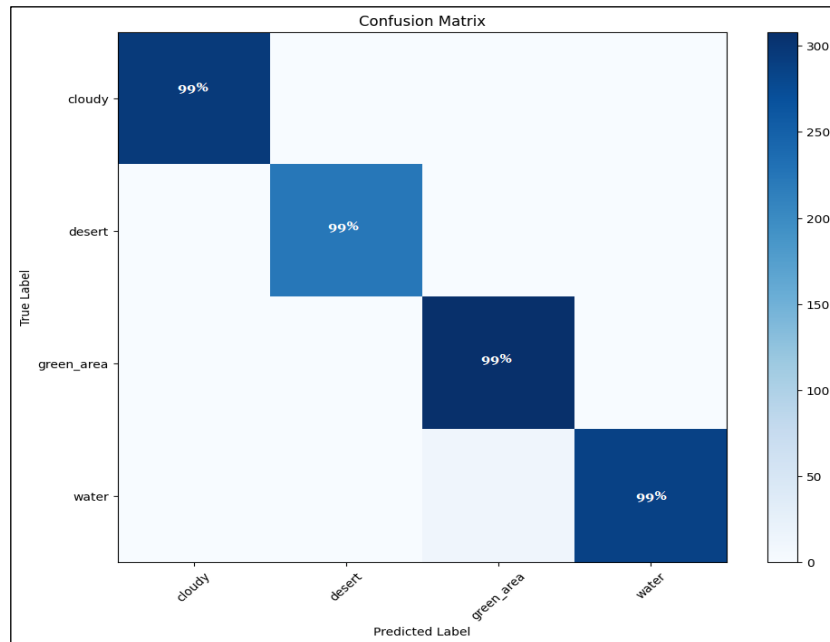


Figure 3: Confusion matrix of the proposed model.
Source: Authors, (2026).

Comparison of Proposed Model and Existing Satellite Image Classifiers

Much research has used various deep learning algorithms to classify satellite images, with the goal of improving accuracy and computing performance. Although the authors stressed that model accuracy varied with dataset complexity, Zare et al. (2017) found encouraging results when using CNN and RNN models for satellite image interpretation. Utilizing densely connected networks on huge and diverse datasets, Li et al. (2020) obtained 92% accuracy for land-use categorization utilizing deeper CNN architectures like DenseNet. Also, while dealing with datasets that are geographically diverse, deeper architectures have continually shown better performance, according to Li et al. (2018), who examined several CNN-based approaches for remote sensing. The benefit of merging alternative learning paradigms was demonstrated by Reddy et al. (2021), who presented a hybrid framework that achieved 95% accuracy by combining deep learning with classical machine learning methods. Famous convolutional neural network (CNN) models, including VGG, AlexNet, and GoogleNet, were compared by Xie et al. (2020). GoogleNet's 90% accuracy was due to its efficient design and better feature extraction capabilities. This study expands upon those earlier efforts by suggesting a hybrid design that combines convolutional neural network (CNN) layers with Vision Transformers (ViT). ViTs are ideal for the complicated task of satellite imaging because of their attention-based mechanism, which allows them to capture both fine-grained local patterns and wider contextual information. To address the ongoing issues with overfitting and improve generalization in satellite image analysis, the suggested model uses strong data augmentation techniques. By utilizing transformer-based representations, the combination of CNNs with ViT attempts to outperform the results reported by established models like DenseNet and ResNet, which generally fall within the 80% to 95% accuracy range, particularly for extremely complex datasets. Beyond just classifying photos, the model also uses beam search to generate meaningful captions, presenting a new dual-capability method. Table 3 summarizes the results of the comparison with existing approaches, while Figure 4 shows the performance of the proposed model.

Table 3: Comparative Analysis of Existing and Proposed Models.

Study / Model	Model/Technique	Dataset Focus	Accuracy (%)
Zare et al. (2017)	CNNs and RNNs	Complex datasets	93%
Li et al. (2020)	DenseNet (deep CNN)	Land-use classification	92%
Li et al. (2018)	Various CNN architectures (review)	Remote sensing datasets	96%
Reddy et al. (2021)	Hybrid of deep learning and ML	Satellite image classification	95%
Xie et al. (2020)	VGG, AlexNet, GoogleNet (CNNs)	Various satellite images	90%
Proposed Model (2025)	ViT + CNN Hybrid + Data Augmentation	Highly complex satellite datasets	99%

Source: Authors, (2026).

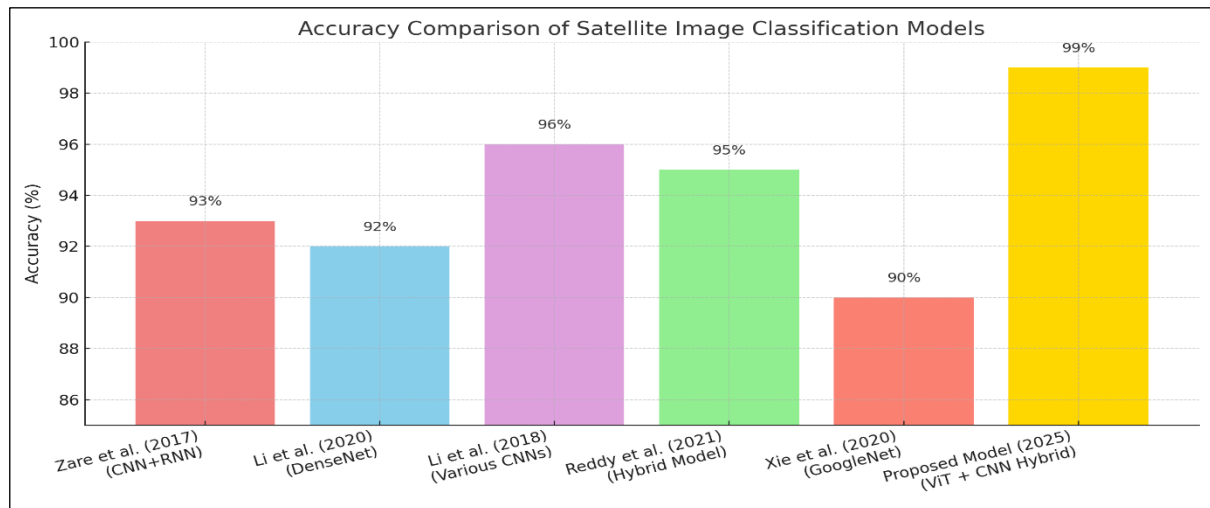


Figure 4: Comparison between existing and proposed models.
Source: Authors, (2026).

V. CONCLUSION AND FUTURE WORK

We presented a model for classifying satellite images that relies on deep learning and makes use of convolutional neural networks (CNNs) to efficiently extract features and classify the images. Data augmentation methods, sophisticated CNN topologies, and optimization tactics all contributed to the model's strong performance on the validation dataset. Results from the suggested model were encouraging, but they may be much better in the future. To further improve accuracy, future work might concentrate on integrating transfer learning with pretrained models such as EfficientNet or ResNet. To further improve the acquisition of spatial and contextual information, it may be worth exploring hybrid techniques that combine CNNs with Vision Transformers (ViTs) or attention processes. One promising area of research is the use of optical and radar data fusion techniques to enhance performance in different environments, and another is the real-time categorization of satellite images for use in environmental monitoring, agriculture, and disaster management.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Potturi Chandrasekhar Raju, Vijay Babu Burra.
Methodology: Potturi Chandrasekhar Raju, Vijay Babu Burra.
Investigation: Potturi Chandrasekhar Raju, Vijay Babu Burra.
Discussion of results: Potturi Chandrasekhar Raju, Vijay Babu Burra.
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Writing – Review and Editing: Potturi Chandrasekhar Raju, Vijay Babu Burra.
Resources: Potturi Chandrasekhar Raju, Vijay Babu Burra.
Supervision: Potturi Chandrasekhar Raju, Vijay Babu Burra.
Approval of the final text: Potturi Chandrasekhar Raju, Vijay Babu Burra.

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