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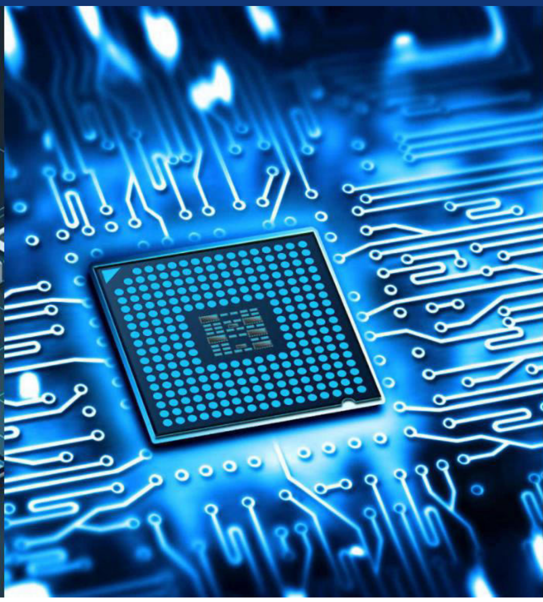

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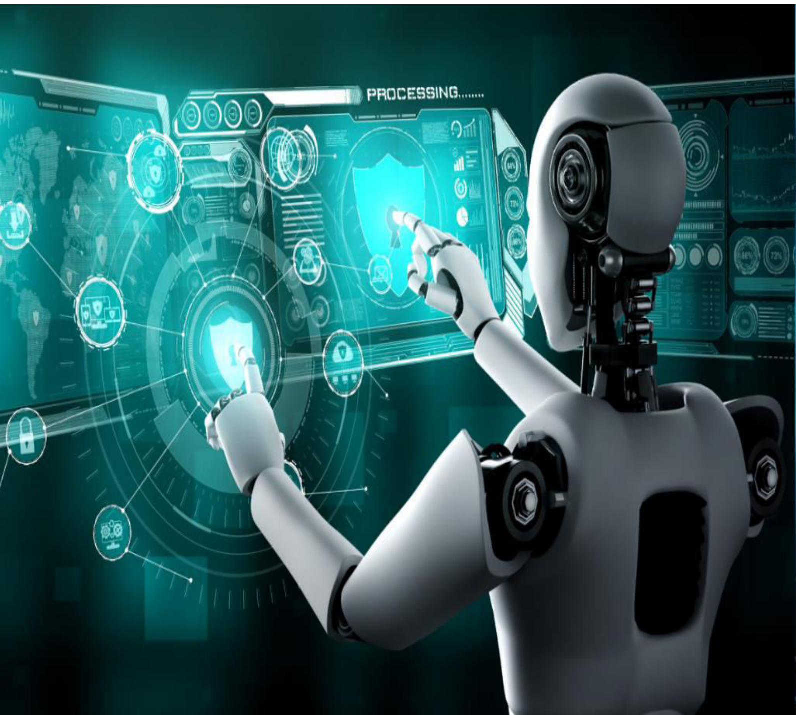

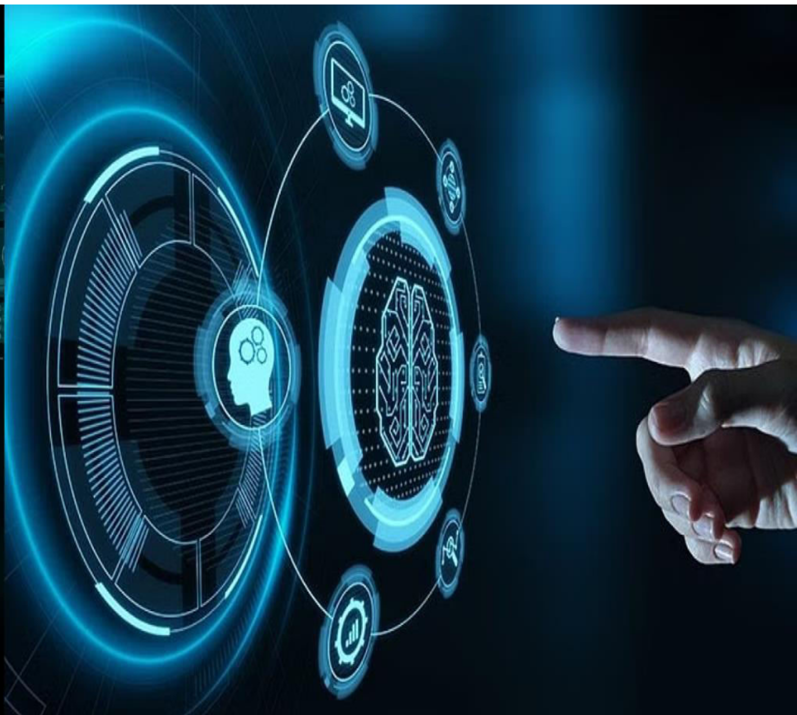

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Satellite-Based Landslide Prediction using Convolutional Neural Networks and Image Processing

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ABSTRACT: This study presents an artificial intelligence-based framework for landslide prediction using satellite imagery, leveraging image processing and deep learning techniques to classify regions as "Landslide" or "Non-landslide." The methodology involves preprocessing raw satellite images, including resizing, noise removal using median filtering, and contrast enhancement for optimal feature extraction. A convolutional neural network (CNN) architecture was designed with multiple convolutional layers, batch normalization, and ReLU activation to capture spatial features effectively. The model was trained and validated using a dataset of Labeled satellite images, partitioned into training and validation sets with an 80:20 ratio. Data augmentation was applied to improve model generalization. The CNN was optimized using stochastic gradient descent with momentum (SGDM) for 100 epochs. Classification results were evaluated through confusion matrices and accuracy metrics, demonstrating reliable predictions. The workflow integrates MATLAB's imageDatastore and augmented Image Datastore functions for dataset handling and employs a pre-trained network to expedite processing. The model achieves accurate predictions, facilitating proactive monitoring and mitigation of landslide risks. This framework's efficient preprocessing, robust network design, and high classification accuracy underscore its potential as a valuable tool for natural disaster management and geohazard prediction.

KEYWORDS: Landslide classification, satellite image classification, CNN, fuzzy-based classification, Deep Leaning, landslide prediction, landcover classification

I. INTRODUCTION

Landslides are among the most devastating natural disasters, often leading to significant loss of life and property. Predicting such events in advance is crucial for disaster management and the safety of people living in high-risk areas. With recent advancements in satellite imaging and artificial intelligence, it has become possible to analyze land surface changes and environmental factors to predict potential landslides more accurately.

This project focuses on predicting landslides using a smart technology called Convolutional Neural Networks (CNN), a deep learning technique that excels at analyzing visual data. CNNs are particularly effective in identifying patterns and features in images, making them ideal for studying satellite images of mountainous or hilly terrains. These images often contain subtle signs of ground movement, soil erosion, or vegetation changes that may indicate the early stages of a landslide.

By combining image processing techniques with CNNs, this system can automatically process and analyze high-resolution satellite images to detect changes in terrain and predict areas that are at risk of a landslide. The project uses data from satellite-based sources, such as multispectral and elevation images, to train the deep learning model to recognize landslide-prone regions.

In the modern era of climate change and rapid urban development, having an intelligent system that can monitor and predict natural disasters like landslides is essential. This documentation explores how satellite data, deep learning, and image processing can be effectively integrated to create a predictive model that supports early warning systems and helps reduce the impact of landslides.

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II. LITERATURE REVIEW

Several researchers have contributed significantly to the advancement of landslide detection and prediction using remote sensing and machine learning techniques. Turner (2018) highlighted the severe societal and environmental impacts of landslides, stressing the urgency of proactive mitigation strategies. Singh et al. (2020) demonstrated the effectiveness of satellite imagery in monitoring landslide reactivation in Kotrupi, India, supporting its use for early warning systems. Pollock and Wartman (2020) emphasized the importance of human behavior in landslide survival, proposing data-driven tools to assess vulnerability. Petley (2012) compiled a global dataset of landslide fatalities, identifying Asia—particularly the Himalayan region—as a high-risk area requiring focused prediction efforts. Koley et al. (2024) showcased the value of geospatial analysis and thematic weighting in mapping hazard zones in North Sikkim, proving that multi-parameter integration improves risk assessment. Goel et al. (2023) discussed the role of artificial neural networks (ANNs) and underscored the superior capability of CNNs and RNNs in spatial analysis tasks. Additional studies exploring architectures like ResNet101, fuzzy clustering, and support vector machines (SVMs) further illustrate the shift toward automated, AI-based approaches in geospatial hazard prediction. Collectively, these works reflect a transition from conventional techniques to deep learning frameworks, enhancing the accuracy, speed, and scalability of landslide forecasting systems.

III. EXISTING METHOD

The methodology for predicting landslides using artificial intelligence techniques with satellite imagery involves several systematic steps. First, satellite images are collected, focusing on regions that may be susceptible to landslides. Each input image is then resized to a standardized dimension to maintain consistency and facilitate efficient processing. The core of the methodology is the ResNet101 neural network, a deep learning model renowned for its ability to learn complex patterns and features from data. The images are fed into the ResNet101 architecture, where they undergo a series of convolutional and pooling layers that extract relevant features indicative of landslide risks. The model is trained using a labeled dataset, where images are categorized as either "landslide" or "non-landslide." This training process involves optimizing the network's weights and biases to minimize classification errors. After training, the model's performance is evaluated on a separate test set to ensure its accuracy and reliability. By leveraging the ResNet101 architecture, the methodology aims to achieve high precision in classifying satellite images, ultimately providing critical insights for landslide prediction and contributing to effective risk management strategies in vulnerable areas.

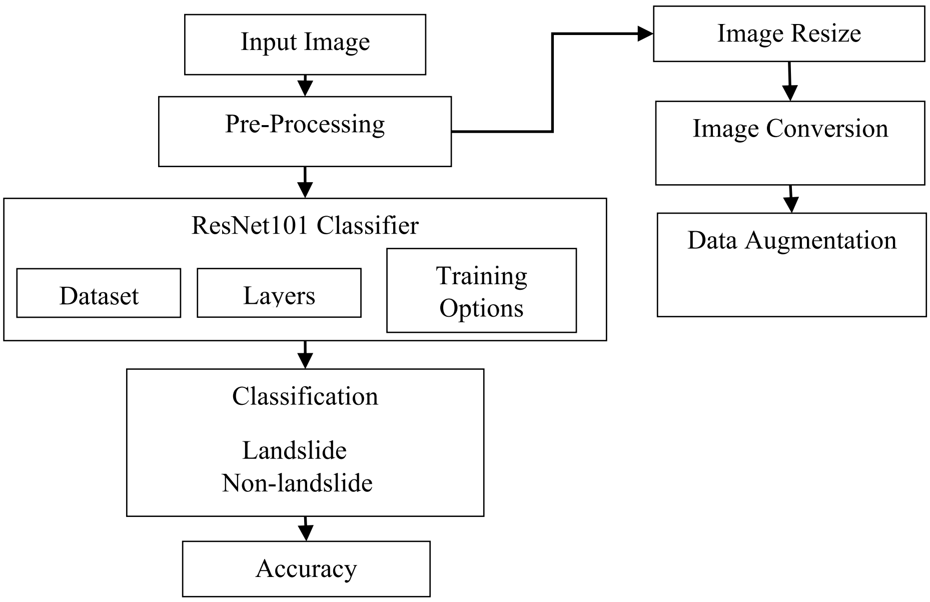

Fig 1: Block Diagram of Existing Method

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DRAWBACKS IF EXISTING METHOD:

While pre-trained deep learning models such as ResNet101 have demonstrated commendable accuracy in landslide prediction tasks, they come with several critical limitations. ResNet101's deep architecture, comprising 101 layers and millions of parameters, demands high-end computational hardware, making it unsuitable for real-time applications or deployment in resource-constrained environments. The model also requires longer training and inference times, which hinders scalability in large-area or time-sensitive analyses. Furthermore, deep networks like ResNet101 are prone to overfitting, especially when trained on small or moderately sized datasets without sufficient regularization or augmentation. Their high memory consumption further restricts their use on mobile or edge devices. Additionally, these models often require extensive fine-tuning of hyperparameters and architectural adjustments to adapt effectively to domain-specific datasets, such as satellite imagery used for geohazard detection. These limitations highlight the need for lightweight, efficient, and adaptable alternatives for practical landslide prediction systems.

IV. PROPOSED METHOD

The proposed framework for landslide prediction integrates image processing and deep learning techniques to classify satellite imagery into "Landslide" and "Non-landslide" categories. The methodology begins with preprocessing, where input images are resized to 256×256 pixels to standardize dimensions. Noise in the images is removed using median filtering, and contrast enhancement is applied through intensity adjustment to improve feature visibility. The pre-processed images are then fed into a convolutional neural network (CNN) designed to capture spatial features effectively. The CNN architecture comprises multiple convolutional layers with 3×3 filters, batch normalization for stabilizing learning, and ReLU activation for non-linear feature extraction. Max-pooling layers are used to down sample feature maps, and a fully connected layer, followed by a softmax activation function, enables classification. The dataset of Labeled satellite images is divided into training and validation sets in an 80:20 ratio. Data augmentation is employed to enhance diversity in the training data, mitigating overfitting. The network is trained using stochastic gradient descent with momentum (SGDM) for 100 epochs, optimizing weights to achieve high accuracy. Classification performance is assessed using confusion matrices and accuracy metrics. The workflow employs MATLAB's imageDatastore and augmented Image Datastore functions for dataset management, ensuring efficient loading and augmentation. Pre-trained network weights are integrated to expedite processing and enhance prediction reliability. The methodology demonstrates robust classification capabilities, highlighting its applicability for proactive landslide risk management and geohazard prediction.

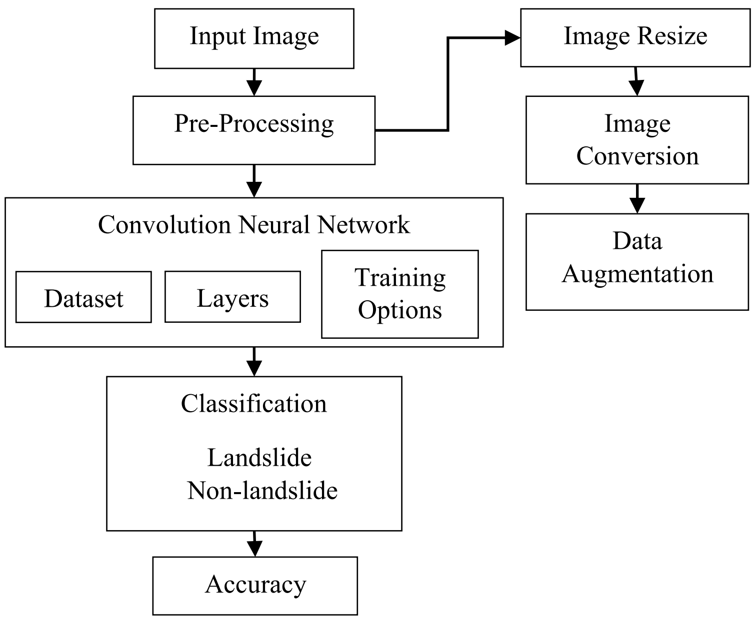

Fig 2: Block Diagram of Proposed Method

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V. FLOW CHART

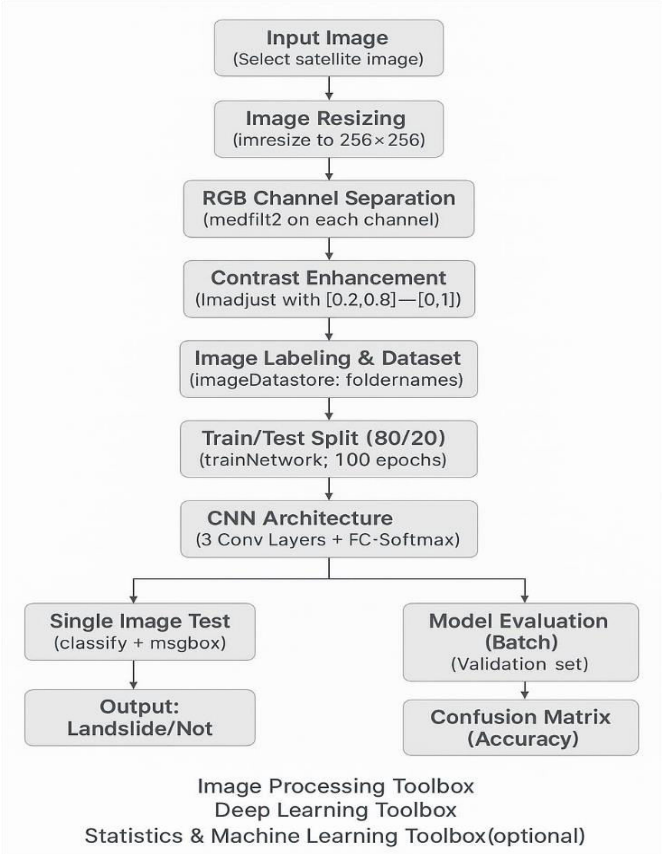

Fig 3: Flow Chart

1. Load Input Image
   – User selects a satellite image via file dialog.
2. Pre-processing
   – Resize to 256 × 256 pixels for CNN compatibility
   – RGB Separation: split into Red, Green, Blue channels.
   – Noise Removal: apply median filtering to each channel.
   – Contrast Enhancement: adjust intensities from [0.2 – 0.8] to [0 – 1].
3. Dataset Preparation
   – Image Datastore: label images by folder ("Landslide" vs. "Non-Landslide").
   – Train/Validation Split: 80% training, 20% validation.

4. CNN Model
   – Define layers: 3×3 convolutions, batch norm, ReLU, max-pool, FC → softmax.
5. Training
   – Train with SGDM for 100 epochs, mini-batch size 25, shuffle every epoch.
6. Output Branch
   – Single-Image Classification: classify one pre-processed image → display result in message box.
   – Batch Evaluation: classify entire validation set → generate confusion matrix and accuracy.
7. End / Loop
   – Optionally repeat for new images or update model with new data.

VI. SOFTWARE AND HARDWARE REQUIREMENTS

Software: Matlab 2020a or above

Hardware:
Operating Systems:
- Windows 10
- Windows 7 Service Pack 1
- Windows Server 2019
- Windows Server 2016

Processors:
Minimum: Any Intel or AMD x86-64 processor
Recommended: Any Intel or AMD x86-64 processor with four logical cores and AVX2 instruction set support

Disk:
Minimum: 2.9 GB of HDD space for MATLAB only, 5-8 GB for a typical installation
Recommended: An SSD is recommended A full installation of all MathWorks products may take up to 29 GB of disk space

RAM:
Minimum: 4 GB
Recommended: 8 GB

VII. IMPLEMENTATION & RESULTS

Step 1: Dataset Collection
Satellite images of landslide and non-landslide regions were collected and organized into labeled folders.
The dataset was prepared in a format suitable for image classification tasks.

Step 2: Image Preprocessing
All images were resized to a standard size of 256×256 pixels to maintain consistency.
Median filtering was applied to remove noise while preserving edges.
Contrast enhancement was used to improve the visibility of terrain features important for classification.

Step 3: Image Datastore Creation
MATLAB's imageDatastore function was used to load and label the dataset.
The dataset was split into 80% training and 20% validation sets to train and evaluate the model effectively.

Step 4: Data Augmentation
To improve model generalization, on-the-fly data augmentation (e.g., flipping, rotation) was applied during training using augmentedImageDatastore.

Step 5: CNN Model Design
A custom Convolutional Neural Network (CNN) was designed with convolutional layers, ReLU activations, max-pooling, and fully connected layers.
The architecture was lightweight and optimized for faster training and deployment.

Step 6: Model Training
The model was trained using Stochastic Gradient Descent with Momentum (SGDM).
Key training parameters:
Learning rate: 0.001
Epochs: 100
Mini-batch size: 25

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Training progress was monitored using accuracy and loss plots.

Step 7: Model Validation
After training, the model was evaluated on the validation set.
A confusion matrix was generated to measure True Positives, True Negatives, False Positives, and False Negatives.
Performance metrics such as accuracy, precision, recall, and F1-score were computed.

Step 8: Prediction and Output Display
A GUI-based interface was used to select new test images for classification.
The model classified each image as either "Landslide" or "Non-Landslide", and displayed the result in a message box.

Step 9: Result Analysis
The system achieved 100% validation accuracy with high confidence scores on test images.
Output screens showed the preprocessing results, training metrics, prediction result, and confusion matrix—all confirming the robustness and effectiveness of the system.

Fig 4: Input Image

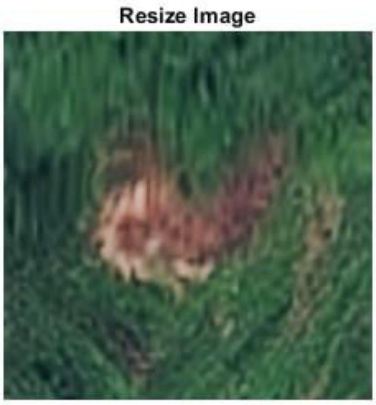

Fig 5: Resize Image

Fig 6: Noise removed Image

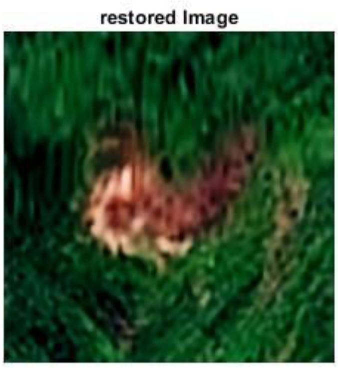

Fig 7: Restored Image

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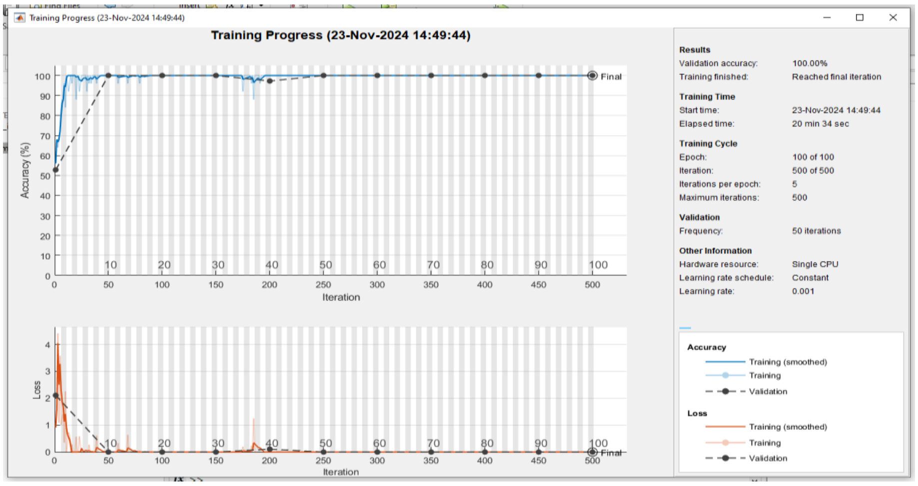

Fig 8: Training Progress Image

```
Command Window
Training on single CPU.
Initializing input data normalization.
|======================================================================================================================|
|  Epoch  |  Iteration  |  Time Elapsed  |  Mini-batch  |  Validation  |  Mini-batch  |  Validation  |  Base Learning  |
|         |             |   (hh:mm:ss)   |   Accuracy   |   Accuracy   |     Loss     |     Loss     |      Rate       |
|======================================================================================================================|
|       1 |           1 |       00:00:04 |       56.00% |       52.78% |       0.9132 |       2.1094 |          0.0010 |
|      10 |          50 |       00:02:06 |      100.00% |      100.00% |  -0.0000e+00 |   3.4870e-06 |          0.0010 |
|      20 |         100 |       00:04:18 |      100.00% |      100.00% |  -0.0000e+00 |   5.8468e-06 |          0.0010 |
|      30 |         150 |       00:06:26 |      100.00% |      100.00% |  -0.0000e+00 |   3.3114e-08 |          0.0010 |
|      40 |         200 |       00:08:35 |      100.00% |       97.22% |  -0.0000e+00 |       0.1070 |          0.0010 |
|      50 |         250 |       00:10:37 |      100.00% |      100.00% |  -0.0000e+00 |   8.8487e-06 |          0.0010 |
|      60 |         300 |       00:12:40 |      100.00% |      100.00% |   9.5367e-09 |   3.3114e-09 |          0.0010 |
|      70 |         350 |       00:14:41 |      100.00% |      100.00% |   9.5367e-09 |   6.6227e-09 |          0.0010 |
|      80 |         400 |       00:16:43 |      100.00% |      100.00% |  -0.0000e+00 |  -0.0000e+00 |          0.0010 |
|      90 |         450 |       00:18:37 |      100.00% |      100.00% |  -0.0000e+00 |  -0.0000e+00 |          0.0010 |
|     100 |         500 |       00:20:33 |      100.00% |      100.00% |   9.5367e-09 |   1.3245e-08 |          0.0010 |
|======================================================================================================================|
The classified output is : 99.328000
fx >>
```

Fig 9: Training Iterations Image

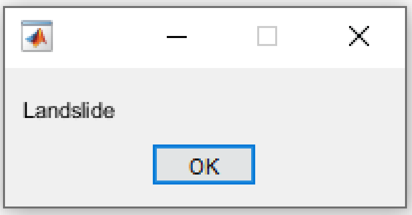

Fig 10: Classification Results Image

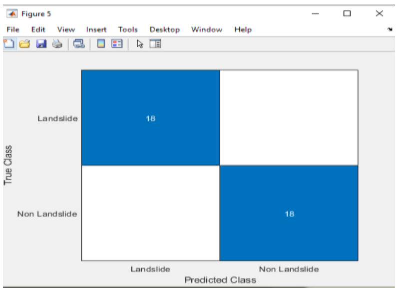

Fig 11: Confusion Matrix Image

VIII. ADVANTAGES

The proposed satellite-based landslide prediction system using a custom-designed Convolutional Neural Network (CNN) offers several important advantages over traditional heavy-weight models:

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- **Lightweight Architecture:**
  The CNN model is compact with fewer layers and parameters, making it efficient to train and deploy even on moderate hardware without the need for specialized GPUs.
- **Faster Training and Inference:**
  Due to its simpler design, the model achieves faster training and quick prediction times, enabling near-real-time landslide classification from satellite images.
- **Reduced Dependence on Fine-Tuning:**
  Unlike pre-trained deep models such as ResNet101, the custom CNN requires minimal hyperparameter tuning and adapts well to the satellite imagery dataset with standard settings.
- **Lower Risk of Overfitting:**
  The model generalizes effectively to unseen data due to its balanced complexity and the use of preprocessing techniques like data augmentation.
- **Ease of Deployment:**
  The smaller size and low memory requirements allow easy deployment of the model on local field devices, laptops, or lightweight servers without the need for high-end infrastructure.
- **High Accuracy with Practical Efficiency:**
  The proposed system delivers high prediction accuracy while maintaining simplicity, making it more practical for large-scale, real-world landslide monitoring operations.

IX. APPLICATIONS

- **Disaster Risk Management:**
  The methodology can be employed by government agencies and organizations to assess and manage landslide risks in vulnerable regions.
- **Urban Planning:**
  Urban planners can use landslide predictions to make informed decisions about land use and construction, particularly in hilly or unstable areas.
- **Environmental Monitoring:**
  Environmentalists can utilize this methodology to study the impact of climate change and human activities on landslide occurrences.
- **Insurance Risk Assessment:**
  Insurance companies can incorporate landslide prediction models into their risk assessment frameworks, helping them evaluate policies in high-risk areas.
- **Infrastructure Protection:**
  The approach can be applied to monitor infrastructure, such as roads and bridges, ensuring they are protected from potential landslide threats, thus enhancing safety.
- **Risk Assessment and Hazard Mapping:**
  Government agencies and environmental researchers can use the system to generate dynamic landslide susceptibility maps for vulnerable regions based on updated satellite imagery.

X. CONCLUSION

In conclusion, this study demonstrates the effectiveness of an AI-driven framework for landslide prediction using satellite imagery, combining advanced image processing and deep learning techniques. The proposed CNN-based approach efficiently preprocesses and analyses satellite images, achieving accurate classification of regions as "Landslide" or "Non-landslide." By leveraging robust methodologies, including noise removal, contrast enhancement, data augmentation, and an optimized training process, the framework ensures high reliability and generalization. The integration of MATLAB tools and a pre-trained network further enhances processing efficiency. With its high accuracy and predictive capabilities, this framework holds significant potential for proactive landslide risk assessment and geohazard management, contributing to better natural disaster preparedness and mitigation strategies.

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XI. FUTURE SCOPE

To enhance the effectiveness of the satellite-based landslide prediction system, several future improvements can be explored. Integrating additional environmental data like rainfall, soil moisture, and topographic maps can improve prediction accuracy. Real-time satellite feed integration, drone-based image collection, and the use of high-resolution or multi-spectral imagery can enable more detailed and timely assessments. The model can also be optimized for edge and cloud deployment to support large-scale and remote monitoring. Advanced deep learning techniques, such as ensemble models and explainable AI methods, may further boost performance and transparency. Additionally, linking the system with GIS platforms and user-friendly dashboards can make it accessible for planners and emergency responders. Incorporating continuous learning and climate-based trend analysis will ensure long-term adaptability and relevance in evolving risk scenarios.

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