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Landslide Susceptibility Mapping using CNN

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Abstract— **Landslide Susceptibility Mapping (LSM) is crucial for identifying regions at risk of landslides, which aids in disaster risk reduction and sustainable land-use planning. Traditional Landslide Susceptibility Mapping methods often rely on complex models needing extensive computational resources, limiting their real-time applicability, especially in remote settings. This study presents an innovative data-driven Landslide Susceptibility Mapping framework that utilizes Convolutional Neural Networks (CNN) to improve mapping efficiency. The Thrissur district in the Western Ghats of Kerala, India, was selected due to its high landslide vulnerability. According to the Landslide Atlas of India (2023), Thrissur is the third most landslide-prone district, facing risks from intense rainfall, rugged terrain, and human activities. This research aims to develop a streamlined and accurate Landslide Susceptibility Mapping framework. A historical landslide inventory was compiled, splitting the data into training (80%) and validation (20%) sets. Various conditioning factors, including topographic, environmental, geological, and proximity variables, are used. A CNN model was then developed and trained, producing a high-resolution landslide susceptibility map with a lightweight architecture suitable for edge device integration. The model exhibited high predictive accuracy, with an Area Under the Curve (AUC) score of 0.987 and a Root Mean Square Error (RMSE) of 0.174. These results highlight the model's effectiveness, offering valuable insights for sustainable land management and disaster mitigation in landslide-prone areas. This research significantly advances Landslide Susceptibility Mapping by combining machine learning with practical applications for environmental risk management. Future work will aim to enhance the framework's scalability and integration into real-time monitoring systems.**

Keywords— Landslide Susceptibility Mapping (LSM), Convolutional Neural Networks (CNN), Landslide Inventory, Machine Learning, Disaster Risk Reduction

I. Introduction

Landslides are among the most devastating natural hazards, causing significant loss of life, damage to infrastructure, and long-term environmental degradation. Globally, landslides result in thousands of fatalities and economic losses amounting to billions of dollars each year. The risk is particularly high in regions with complex terrain, fragile geological formations, and intense rainfall patterns. India, owing to its varied physiography and monsoonal climate, is highly susceptible to landslides, especially along the Himalayan belt and the Western Ghats. In this context, the state of Kerala, located in the southwestern part of India, experiences frequent landslides, particularly during the monsoon season. The Thrissur district, situated in the Western Ghats region of Kerala, has emerged as one of the most vulnerable districts, as identified by the Landslide Atlas of India (2023), ranking third in terms of landslide-prone areas. The district's rugged topography, combined with anthropogenic pressures such as deforestation, quarrying, and unplanned urban expansion, exacerbates its susceptibility to slope failures.

Landslides are triggered by a complex interplay of geological, geomorphological, hydrological and anthropogenic factors. These include steep slopes, weak lithological formations, high-intensity rainfall, land-use changes, and inadequate drainage systems. Understanding and predicting where landslides are likely to occur—referred to as landslide susceptibility mapping (LSM)—is crucial for informed decision-making in disaster risk reduction, infrastructure planning, and sustainable development. Over the years, various approaches have been developed for Landslide Susceptibility Mapping, ranging from qualitative methods like expert-based heuristic assessments to quantitative models such as bivariate statistics, Logistic Regression, and the Analytical Hierarchy Process (AHP). While these traditional models have contributed significantly to the field, they often rely on linear assumptions and may not fully capture the intricate, non-linear relationships among causative factors.

With the emergence of machine learning and artificial intelligence, data-driven models have gained prominence in Landslide Susceptibility Mapping. Among these, Convolutional Neural Networks (CNNs)—a class of deep learning models—have shown exceptional capabilities in learning spatial hierarchies and complex patterns from high-dimensional data. Originally developed for image classification tasks, CNNs are now widely applied in various geospatial applications due to their ability to process raster data effectively. In the context of Landslide Susceptibility Mapping, CNNs can learn from spatial patches of terrain

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data, capturing local features and contextual relationships that traditional models may overlook. Their scalability and capacity to generalize well across diverse landscapes make them particularly suitable for landslide prediction in data-rich environments.

II. Literature review

In recent years, the application of machine learning and deep learning techniques has gained significant momentum in the field of landslide susceptibility mapping (LSM). Among these, Convolutional Neural Networks (CNNs) have emerged as a powerful tool due to their ability to automatically learn spatial features from complex geospatial data. A notable study applied CNNs with multi-scale sampling strategies to enhance prediction accuracy, showcasing the model's ability to capture spatial variability in landslide-prone areas [1]. Additionally, CNN-based approaches have shown superiority in integrating topographic, geological, and hydrological factors for landslide prediction, outperforming conventional models like Decision Trees and Support Vector Machines (SVM) [2]. The adoption of CNNs has led to more precise and reliable susceptibility maps, as evidenced by successful applications in regions such as Wayanad, Kerala [3]. The CNN model used in the study for national-scale landslide susceptibility mapping of Iran consisted of multiple convolutional, activation (ReLU), and pooling layers designed to efficiently extract spatial features from geospatial input data.

It achieved good performance with an AUC of 0.85, demonstrating its ability to learn from terrain and environmental variables, though slightly less accurate than the RNN model used for comparison [4]. These studies collectively illustrate the versatility and effectiveness of CNN-based approaches for Landslide Susceptibility Mapping. The integration of multi-scale sampling and CNNs has substantially enhanced the accuracy of predictions, paving the way for more precise risk assessments [5][6][7].

CNNs have also been effectively combined with GIS-based spatial analysis, resulting in improved mapping performance and automation of susceptibility zoning [8]. These deep learning frameworks allow better generalization to unseen data, especially in mountainous or data-scarce regions [9]. Moreover, studies have reported that CNN architectures can be customized to process multi-source input layers such as slope, elevation, land use, and rainfall intensity, allowing for a more comprehensive susceptibility model [10].

Despite the growing interest in applying CNNs to landslide mapping, limited studies focus on the rugged terrain of Kerala, where landslide occurrences are frequent and often devastating. This study aims to address this gap by developing a CNN-based landslide susceptibility model specifically for the Thrissur district. By leveraging DEM-derived factors and validating the model using Area Under the Curve and Root Mean Square Error, this research aims to provide accurate, data-driven insights for landslide risk assessment.

III. Methodology

The methodology for landslide susceptibility mapping in the Thrissur district is a comprehensive process that integrates various environmental and geological factors. The initial stage involves identifying and gathering critical elements that influence landslide occurrences, such as annual rainfall, elevation, slope, aspect, and lithology. Additional parameters include profile curvature, plan curvature, and several indices like the Topographic Position Index (TPI), Topographic Wetness Index (TWI), Stream Power Index (SPI), and Sediment Transport Index (STI).

To derive these factors, Digital Elevation Model (DEM) data from the US Geological Survey is processed, while historical records and field surveys are utilized to prepare a landslide inventory map that marks past occurrences. Once the data is collected, it undergoes a preprocessing stage where the DEM-derived factors are standardized to ensure consistency across dimensions. As shown in Fig. 1, the slope map indicates the variation in slope across the study area, which is a significant factor in landslide susceptibility analysis.

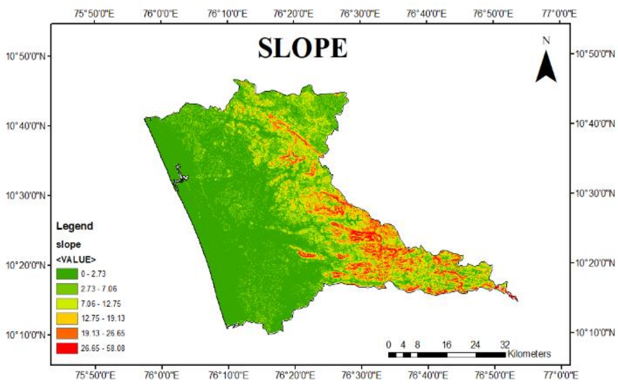

Fig. 1. Slope map

The aspect map (Fig. 2) displays the orientation of slopes, which influences surface runoff and soil erosion. According to the lithology map (Fig. 3), the study area comprises diverse geological formations, which impact slope stability. The plan curvature map (Fig. 4) and profile curvature map (Fig. 5) illustrate the concavity and convexity of the terrain, respectively, which are essential in understanding water flow dynamics. Fig. 6 shows the Stream Power Index (SPI) map, highlighting areas with high erosive power, while Fig. 7 represents the Sediment Transport Index (STI), indicating the potential for sediment displacement. The Topographic Position Index (TPI) map (Fig. 8) highlights the relative elevation of terrain features, distinguishing between ridges, valleys, and flat areas, which are crucial for understanding geomorphological patterns. The Topographic Wetness Index (TWI) map (Fig. 9) illustrates areas with higher moisture accumulation, which is an essential factor in evaluating landslide susceptibility.

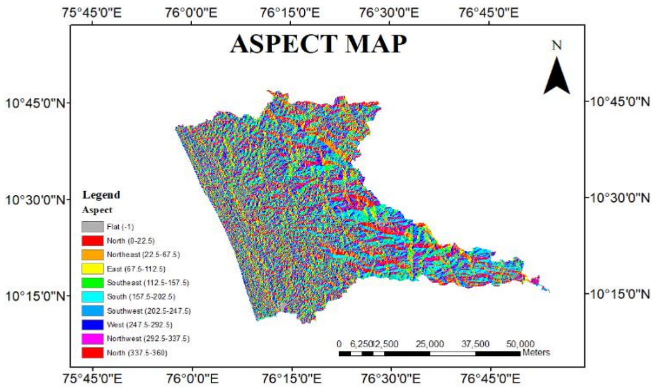

Fig. 2. Aspect map

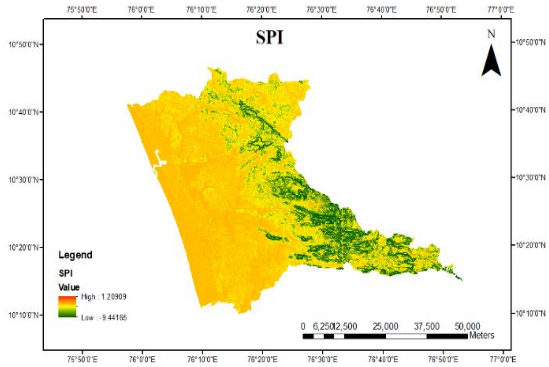

Fig. 6. Stream Power Index map

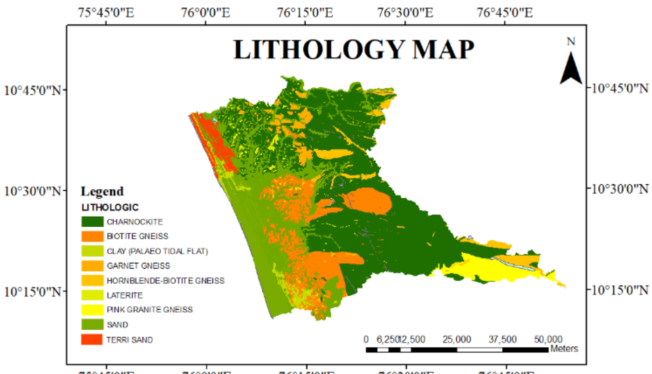

Fig. 3. Lithology map

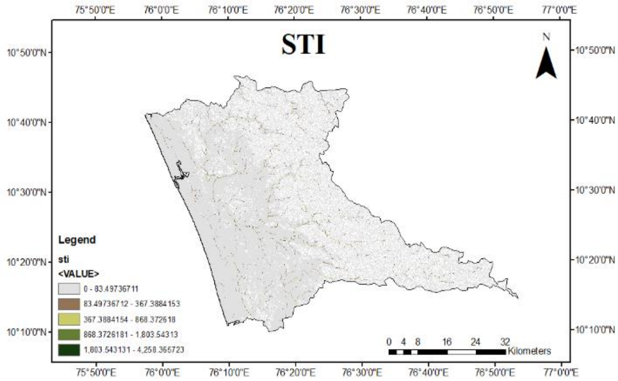

Fig. 7. Sediment Transport Index map

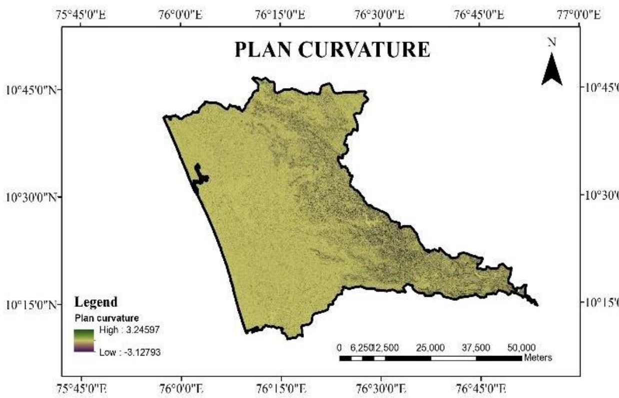

Fig. 4. Plan Curvature map

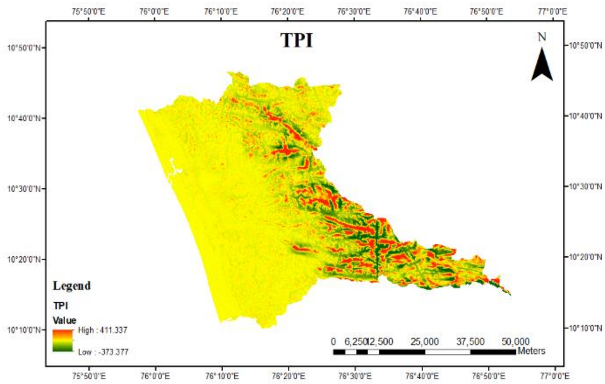

Fig. 8. Topographic Position Index map

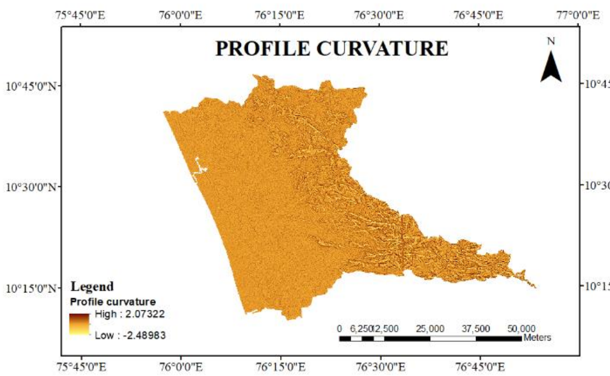

Fig. 5. Profile Curvature map

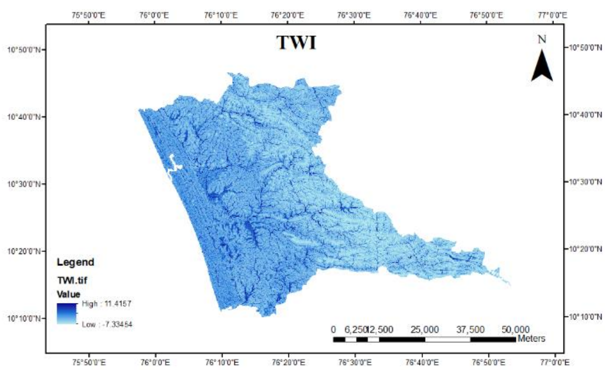

Fig. 9. Topographic Wetness Index map.

To enhance the robustness of the model, data augmentation techniques, including adding noise and transformations, are employed. This refined dataset is subsequently divided into training and validation sets, with 80% allocated for training and 20% for validation to maintain a balanced representation of the data.

A Convolutional Neural Network (CNN) was implemented to predict landslide susceptibility by analyzing spatial patterns within small terrain patches. The model was specifically designed to extract hierarchical spatial features through multiple convolutional layers. The input to the CNN consisted of 5×5×9 patches, where each patch represents a 5×5 pixel grid centered on a landslide or non-landslide location, and the nine channels correspond to nine conditioning factors: slope, aspect, profile curvature, plan curvature, lithology, Topographic Wetness Index (TWI), Stream Power Index (SPI), Topographic Wetness Index and Topographic Position Index (TPI) [6].

Each pixel within a patch contains the corresponding value for these nine factors, allowing the CNN to learn complex spatial relationships and topographic signatures associated with landslide occurrences. The features are selected based on their significance concerning landslide risks and their availability within the study area. The architecture of the Convolutional Neural Network used for landslide susceptibility prediction is shown in Fig. 10, illustrating the feature extraction and classification stages.

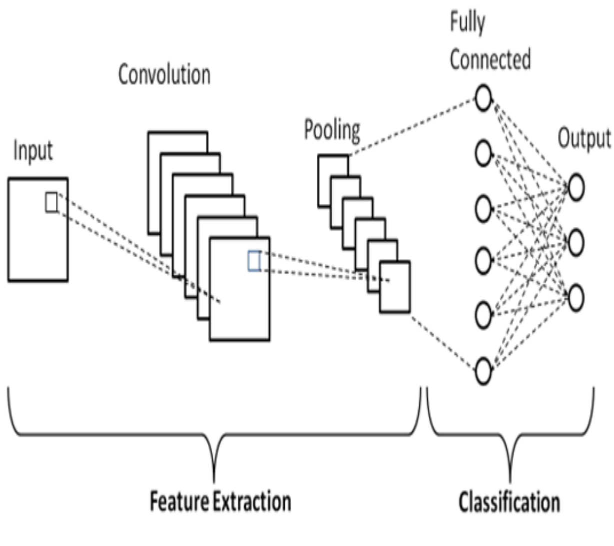

Fig. 10 CNN Architecture

The CNN consists of three convolutional layers, each followed by batch normalization, dropout, and max-pooling operations. The progressive filtration employs 32, 64, and 128 filters in the layers, enabling the model to capture patterns ranging from low-level details to more complex features. Batch normalization aids in stabilizing the training process, while dropout is utilized to mitigate the risk of overfitting. The max-pooling layers serve to compress the spatial dimensions while preserving crucial features.

Following the convolutional sequence, a flatten layer transforms the multidimensional output into a one-dimensional vector, leading to a dense layer composed of 256 neurons. This layer is instrumental in learning intricate patterns, with dropout applied again to improve generalization. The final layer of the CNN model is a fully connected output layer with a single neuron that uses a sigmoid activation function. This configuration allows the model to produce a probability value between 0 and 1 for each input patch, representing the likelihood of landslide occurrence. A value closer to 1 indicates a high susceptibility, while a value closer to 0 indicates a low susceptibility. These probability scores are then used to generate a continuous landslide susceptibility map across the study area. The CNN model is trained using stochastic gradient descent to minimize binary cross-entropy loss, and its performance is assessed through metrics like Area Under the Curve (AUC) and Root Mean Square Error (RMSE) to ensure reliable predictions.

Once the modeling phase is complete, the landslide susceptibility mapping is performed by integrating the spatial predictions generated by the CNN. An essential component of the methodology is model validation, where the accuracy of the trained model is scrutinized using Area Under the Curve and Root Mean Square Error metrics. This validation process compares the predicted outcomes against actual landslide occurrences to confirm the model's accuracy. Furthermore, a comparative analysis is conducted between the CNN-based model and traditional methodologies like Logistic Regression and Decision Trees, demonstrating the advantages of the CNN approach in effectively managing complex spatial relationships.

IV. Results and Discussion

Figure 11 illustrates the landslide susceptibility map generated using the trained CNN model. The susceptibility scores range from 0 (low) to 1 (high), with warmer colors (yellow to red) representing areas of higher landslide risk. The model clearly identifies high-susceptibility zones along the central and eastern slopes of the study area, which align well with known landslide-prone regions.

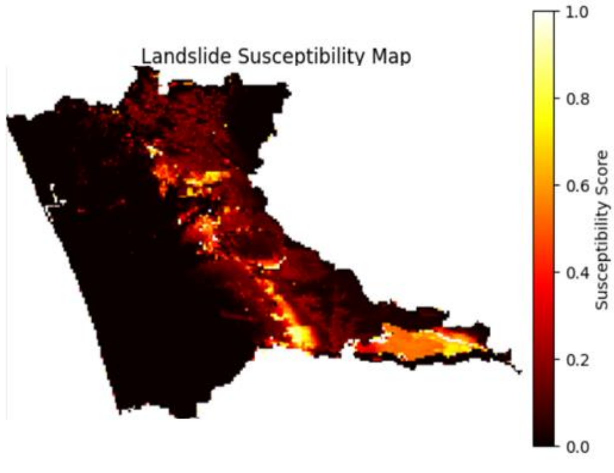

Fig. 11. Landslide Susceptibility map

The spatial distribution of susceptibility shown in Figure 10 demonstrates the CNN model's ability to detect patterns associated with terrain instability. High-risk areas correlate strongly with steep slopes, high SPI and TWI values, and weak lithological formations, validating the model's effectiveness in capturing key landslide-driving factors. Moreover, the continuous probability scale supports a more nuanced interpretation of risk compared to binary classification methods.

The convolutional neural network (CNN) model developed for assessing landslide susceptibility in the Thrissur district has exhibited remarkable predictive capabilities, as highlighted by a high Area Under the Curve (AUC) score of 0.987 (Fig. 12). This impressive performance metric underscores the model's proficiency in distinguishing between areas that are susceptible to landslides and those that are not. The Receiver Operating Characteristic (ROC) curve associated with the model illustrates a pronounced ascent toward the top-left corner, indicative of a high true positive rate combined with a minimal false positive rate, which are both critical factors in effective risk assessment.

The model's Root Mean Square Error (RMSE) value of 0.1747 further reinforces its accuracy in predicting landslide susceptibility, suggesting that errors in the model's predictions are quite low, thereby enhancing its overall reliability. Additionally, the success rate AUC of 0.993, along with the prediction rate AUC of 0.987, signifies not only the model's robust generalization capabilities but also its effectiveness in accurately delineating susceptibility zones within the study area.

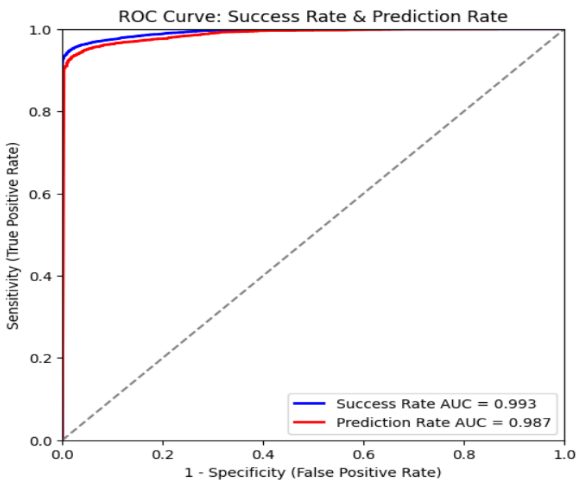

Fig. 12. ROC-AUC Curve

In comparison to traditional analytical techniques, such as Logistic Regression and Decision Trees, the CNN approach demonstrates superior performance. Conventional methods typically face challenges in capturing the complex and multifaceted spatial patterns associated with landslide occurrences. The CNN's inherent ability to learn from these spatial dependencies contributes significantly to the enhanced accuracy of landslide susceptibility mappings.

Furthermore, the generated landslide susceptibility map aligns closely with documented historical landslide events, thereby validating the model's practical application in disaster risk management. This innovative tool can assist local authorities in pinpointing high-risk areas, thereby enabling the implementation of more targeted and effective mitigation strategies.

In summary, the incorporation of CNN technology in the realm of landslide susceptibility mapping marks a significant leap forward in comparison to conventional methodologies. This advancement not only provides improved precision but also elevates the reliability of identifying regions that are prone to landslides, ultimately contributing to enhanced safety and risk management in vulnerable areas.

V. CONCLUSION

The study triumphantly unveiled a cutting-edge, CNN-based model for mapping landslide susceptibility across the beautiful landscapes of the Thrissur district. This innovative model achieved remarkable predictive accuracy, as highlighted by impressive Area Under the Curve and Root Mean Square Error values. By adeptly capturing intricate spatial relationships, it significantly elevates the accuracy of landslide predictions, far surpassing traditional methods.

The resulting susceptibility map provides invaluable insights for disaster risk management and land-use planning, serving as a vital tool for decision-makers. This proactive approach allows for the implementation of measures designed to reduce the devastating impacts of landslides on communities and the environment. Looking ahead, future research could delve into the incorporation of additional geospatial factors and explore the model's application in diverse regions, broadening its potential and effectiveness in safeguarding vulnerable areas.

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