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RESEARCH PAPER

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Leveraging CNNs-RNNs and Adam Optimization: A Revolutionary Deep Learning approach to landslide prediction in district of Than Uyen, Lai Chau province, Vietnam

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*Abstract**:*** This paper presents an innovative deep learning framework for predicting landslides in the District of Than Uyen, Lai Chau Province, Vietnam, harnessing the power of Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and the Adam Optimization algorithm. Given the multifaceted nature of landslide phenomena, influenced by a myriad of geographical and meteorological factors, there is a growing need for advanced computational strategies that can decipher complex patterns and temporal correlations.

Our cutting-edge model employs CNNs to analyze and extract significant spatial attributes from topographical and geological data. Concurrently, RNNs -specifically Long Short-Term Memory (LSTM) networks - are deployed to manage time-series data, such as weather conditions and other temporal elements. The Adam Optimization algorithm, renowned for its superior efficiency and effective performance, is used to optimize the model parameters.

The model was trained and validated using a comprehensive dataset from the Than Uyen district, comprising 114 landslide and 114 non-landslide locations, along with ten key influential factors: elevation, slope, curvature, aspect, relief amplitude, soil type, geology, and proximity to faults, roads, and rivers. The results demonstrate a noteworthy predictive accuracy, sensitivity, and specificity, with the model surpassing benchmarks in prediction power (PPV=93.3%, NPV=83.2%, Sen=82.3%, Spe=94.1%, Acc=88.2%, F-score=0.875, Kappa=0.765, and AUC=0.968).

The study advances deep learning in landslide prediction, aiding proactive disaster mitigation and showing potential for application in global regions prone to geographical hazards.

Keywords: Deep Learning, Landslide, CNNs, RNNs, Adam

I. INTRODUCTION

Landslides, a significant geohazard, contribute to thousands of fatalities and inflict damage amounting to $100 million annually on a global scale [1,2,3]. The rise in extreme weather phenomena such as heavy rainfall and typhoons [4,5], particularly in the mountainous regions of developing nations, is anticipated to increase the frequency of landslides [6]. Being situated in Southeast Asia, one of the world's most disasterprone regions [7], Vietnam is particularly vulnerable. Therefore, accurate spatial prediction of landslides is crucial for risk mitigation.

Machine learning methods have been gaining precedence over statistical methods in landslide susceptibility mapping, as suggested by various studies [8,9,10,11,12,13,14]. This preference stems from the expansive availability of geospatial data along with the evolution of machine learning and optimization algorithms on open-source platforms like Python [15] and Google TensorFlow [16]. This trend is evident when the task involves handling numerous influencing factors and limited landslide data [17].

Ensemble modeling, which combines multiple models into a final comprehensive model, has enhanced the reliability of landslide susceptibility mapping [18,19,20,21]. Among various machine learning algorithms, ensemble learning stands out due to its unique capability of integrating multiple deep learning models. This method aims to enhance diverse aspects of deep learning, including pre-dictions and classifications, by not just merging the unique capabilities of individual deep learning models but also potentially creating a hybrid model that encapsulates the collective attributes of its components [21].

To address these needs, we propose a method that we will validate through a case study in the Than Uyen district of the Lai Chau province in Vietnam, an area plagued by recurring landslides. We will compare our method against four benchmark models including Convolutional Neural Networks (CNNs) [22], Re-current Neural Networks (RNNs) [23], Multi-Layer Perceptron Neural Network (MLPNeuNet) [24], and the BBO-DE Optimized SPAARCTree Algorithm (BBO-DE-STreeEns) [25]. These models were optimized with the same optimizer namely Adaptive Moment Estimation (Adam) [26].

This paper is structured as follows: Section 2 reviews the background of the employed methods. Section 3 describes the study area and landslide database. Section 4 details the proposed ensemble learning method utilized for landslide susceptibility derivation. Section 5 reports the experimental results, followed by a discussion. The final section presents the concluding remarks.

II. BACKGROUND OF METHODS USED

In this study, we investigated the effectiveness of ensemble learning, a method that combines multiple deep learning models, aims to enhance prediction, classification, or other functionalities within the scope of deep learning. It not only amalgamates the unique capabilities of different deep learning models but can also create a hybrid model enriched with the combined features of its constituent models [25]. Choosing to develop such an ensemble model has several advantages over designing a new model entirely from the ground up:

Efficient Data Utilization: Ensemble learning can leverage the knowledge gained from the constituent models, thereby requiring minimal data for training the combined model.

Time-Efficiency: The construction of an ensemble model typically demands less time in comparison to the process of building a fresh model.

Resource Optimization: The amalgamation of models into an ensemble is generally less computationally intensive.

Enhanced Performance: The resultant ensemble model usually exhibits higher accuracy and capabilities, surpassing the individual models it comprises

A. *Convolutional Neural Networks (CNNs)*

Convolutional Neural Networks (CNNs) [22] are a potent category of deep learning algorithms extensively used for diverse image and video processing tasks. These include object recognition, image classification, and object detection. CNNs are specifically designed to efficiently analyze and extract meaningful information from gridlike structured data, such as images. They leverage the convolution concept, which allows the network to recognize local patterns and features within the input data. This unique trait makes CNNs highly proficient in learning and identifying intricate visual patterns autonomously, making them an invaluable asset in computer vision applications.

The core principle of CNNs involves the application of convolutional layers, pooling layers, and fully connected layers to extract pertinent features from the input data. The convolutional layers use adjustable filters or kernels to scan the input data, performing convolutions that assist in identifying local patterns or features. These convolutions produce feature maps that represent distinct facets of the input data.

In this study, Convolutional Neural Networks (CNNs) were leveraged through the Conv1D layer of Keras. Specifically, the model incorporated two Conv1D layers, each with 64 filters and a kernel size of 3. Additionally, the model used the Rectified Linear Unit (ReLU) activation function in both Conv1D layers.

B. *Recurrent Neural Networks (RNNs)*

Recurrent Neural Networks (RNNs) [23] represent a unique class of artificial neural networks specifically engineered to process sequential or temporal data. They achieve this by integrating feedback connections, a feature which distinguishes them from traditional feedforward neural networks. In an RNN, connections are designed in such a way that information from previous time steps can be transmitted to the current time step. This capability allows RNNs to capture temporal dependencies in the data, effectively handling input sequences of different lengths.

The underlying structure of RNNs allows them to remember or 'recollect' information from previous time steps in the sequence. This 'memory' is stored in hidden states, which are updated at each time step based on both the current input and the previous hidden state. Hence, the hidden state serves as a kind of 'context' that captures the information seen by the network so far in the sequence.

In the scope of this research, the authors have employed Recurrent Neural Networks (RNNs) using the LSTM (Long Short-Term Memory) layer of the Keras library. LSTMs represent an advanced variant of RNNs that were developed to address the notable issue of gradient vanishing or exploding, which is often encountered during the training of traditional RNNs. LSTMs introduce a more complex structure in the recurrent units, including a memory cell and several gating units, which collectively enable the model to learn and remember over long sequences and effectively tackle the challenge of long-term dependencies

C. *The Adam Optimizer Algorithm*

The Adam optimizer algorithm is a widely adopted optimization technique used in deep learning. Its name originates from the term Adaptive Moment Estimation (Adam) [26]. The algorithm is a fusion of two other optimization methods - the Adaptive Gradient Algorithm (AdaGrad) and the Root Mean Square Propagation (RMSprop). By merging the best features of AdaGrad and RMSprop, Adam provides an efficient way to adjust learning rates for different parameters during the training process of a neural network. This adaptive learning rate optimization algorithm is beneficial in accelerating convergence and enhancing the overall performance of the neural network.

The key idea behind the Adam optimizer is that it computes adaptive learning rates for different parameters. It stores an exponentially decaying average of past gradients (like momentum) and keeps an exponentially decaying average of past squared gradients (similar to RMSprop). Adam then uses these averages to scale learning rates for each weight in the neural network model.

The Adam optimizer is not just efficient but also requires minimal memory and computational resources, making it a popular choice in the field of deep learning. It's suitable for problems that are large in terms of data and/or parameters. The algorithm's ability to handle sparse gradients on noisy problems is also a reason why Adam is a great choice when dealing with neural networks.

III. STUDY AREA AND LANDSLIDE DATA

A. *Description of the Study Area*

Than Uyen district, located in southeast Lai Chau province in northwest Vietnam. It is positioned between longitudes 103°35’E and 103°53’E, as well as latitudes 21°40’N and 22°08’N, covering an area of 792.53 km2 (Fig. 1). Than Uyen lies within the Nam Mu river basin, which is a level-1 tributary of the Da River, and features medium-high mountains and complex terrain, with high river and stream density. It comprises three areas: the rugged Fansipan range to the east, low Pu San Cap mountains to the west, and a central valley of hills, plains, and mountains [27,28].

The district experiences a monsoonal climate with distinct rainy (April-October) and dry (November-March) seasons, featuring average annual rainfall of 1800-2200 mm, temperatures of 22-23 °C, and around 80% humidity. The road network includes key routes linking to Lai Chau city and other provinces, but its winding roads make it landslide-prone during the rainy season [28].

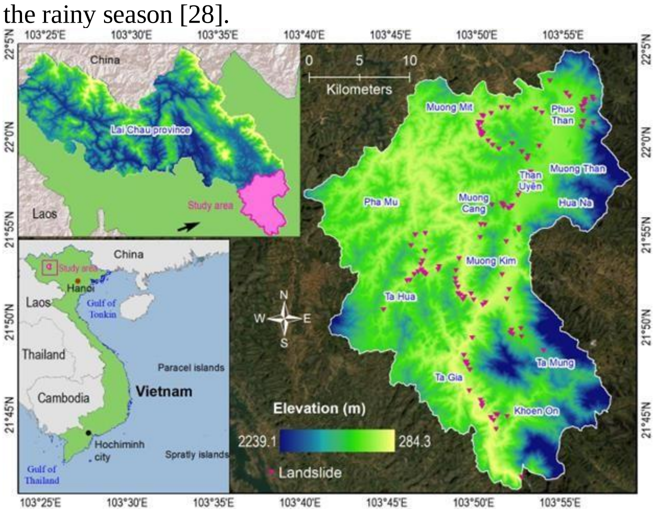

Figure 1. Location of Than Uyen district Source [25]

The area is tectonically active with faults leading to intense weathering and rock disintegration, creating unstable zones prone to landslides. Its geology is divided into several complexes based on petrological composition and stability.

As of December 31, 2017, the population of Than Uyen district was 66,589, with a total of 13,838 households, out of which 3,340 were classified as poor. Unfortunately, some residents of the district have built their homes along roads, directly beneath roadside slopes that pose a significant risk of landslides [28]

In recent times, Than Uyen has emerged as a region significantly impacted by natural calamities, especially landslides. These landslides are triggered by a complex interplay of natural, environmental, and societal elements. Notably, the development of new infrastructures like roads and urban zones in the region has been pinpointed as a key factor exacerbating landslide occurrences due to human intervention. [27,29].

B. Landslide Data

1) Historical Landslides.

The landslide inventory map of Than Uyen district (Figure 1) stems from the "Investigation, Assessment, and Warning Zonation for Landslides in the Mountainous Regions of Vietnam" project, funded by the Vietnamese government and initiated by the Vietnam Institute of Geosciences and Mineral Resources in 2012 [27,28].

Using air photo interpretation, 3D relief analysis with 1:10,000 topographical maps, satellite and radar imagery, and field surveys, the project identified 114 landslides in Than Uyen district over the past decade, primarily triggered by rainfall [27,28]. These landslides are concentrated along slopes adjacent to National Road 279 (from Sap Nguoi village to Khau Co pass), Provincial Road 106 (from Muong Kim to Khoen On), and intercommune roads linking Muong Kim to Ta Mung and Than Uyen to Pha Mu. No landslides triggered by earthquakes were observed during the study period.

Field research and analysis revealed that landslides were mainly caused by heavy thunderstorms, especially when daily rainfall exceeded 100 mm. Such events lead to water saturation of the soil and rock mixture on slopes, reducing shear strength and causing instability. Figure 2 provides photos of a landslide in the study area.

Figure 2. Two photos of the landslide on the slope wall of National Road 279, near the right bank of Nam Kim stream, Na Pa village, Muong Kim commune, Than Uyen district. Source: Vietnam Institute of Geosciences and Mineral Resources [29]

2) Landslide Influencing Factors

To analyze landslides in the study area, we considered 10 influential factors: elevation, slope, curvature, aspect, relief amplitude, soil type, geology, distance to faults, distance to roads, and distance to rivers. These factors, known to impact slope stability and landslide risk [25], were mapped as follows:

Elevation: Affects slope angle, gravitational force, climate, and vegetation. Derived from a DEM based on 1:50,000 topographic maps (Figure 3a).

Slope: Steeper slopes are more susceptible to landslides. Generated from the DEM (Figure 3b).

Curvature: Indicates changes in slope angle and direction; higher absolute curvature areas are riskier. Generated from the DEM (Figure 3c).

Aspect: Influences environmental factors like rainfall and soil moisture. Mapped into nine classes from the DEM (Figure 3d).

Relief Amplitude: Reflects gravitational potential energy. Created in ArcGIS Pro (Figure 3e).

Soil Type: Affects water drainage and slope stability. Based on a 1:100,000 pedology map with 11 soil types (Figure 3f).

Geology: Determines rock types and structures affecting stability. Derived from a 1:200,000 geology map showing 12 units (Figure 3g).

Distance to Faults: Categorized distances from 0-200m to >1000m from a 1:200,000 scale map (Figure 3h).

Distance to Roads: Categorized distances from 0-40m to >120m from 1:50,000 scale maps (Figure 3i).

Distance to Rivers: Categorized distances from 0-40m to >120m from 1:10,000 scale maps (Figure 3j).

These maps collectively provide a comprehensive assessment of factors influencing landslide risk in the area.

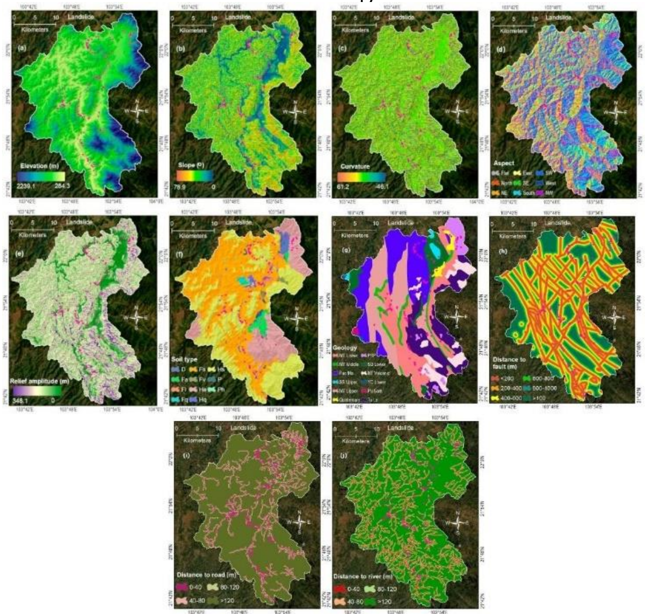

Figure 3. Landslide influencing factors: (a) Elevation; (b) Slope; (c) Curvature; (d) Aspect; (e) Relief amplitude; (f) Soil type; (g) Geology; (h) Distance to fault; (i) Distance to road; and (j) Distance to river. Source [25]

C. The proposed ensemble learning model for Landslide prediction

The flowchart for the proposed CNNs-RNNs method for landslide susceptibility mapping is illustrated in Fig. 4. To derive the landslide inventory and influencing factors, multisource geospatial data were processed using ArcGIS Pro 2.8 and stored in a landslide database in file geodatabase format. The influencing factors were converted to a 20m×20m grid cell and normalized within the range of [0.001–0.999]. The CNNs-RNNs model was implemented by the authors in Python.

1) The Landslide Database

The study encompassed 114 distinct landslide locations, which were randomly segmented into two groups: a training set with 80 cells, constituting 70% of the total, and a validation set of 34 cells of the remaining. All landslide cells were assigned a value of '1'. To prevent bias due to unequal distribution of landslide and non-landslide data, an equivalent number of grid cells were randomly selected from non-landslide areas. These cells were assigned a value of '0' and integrated into the training and validation datasets. As a result, both the training and validation sets had an even distribution of 160 and 68 samples respectively, ensuring a balanced number of landslide and nonlandslide pixels within each set. The training set was employed to develop the landslide models, and the validation set was utilized to assess their accuracy and reliability.

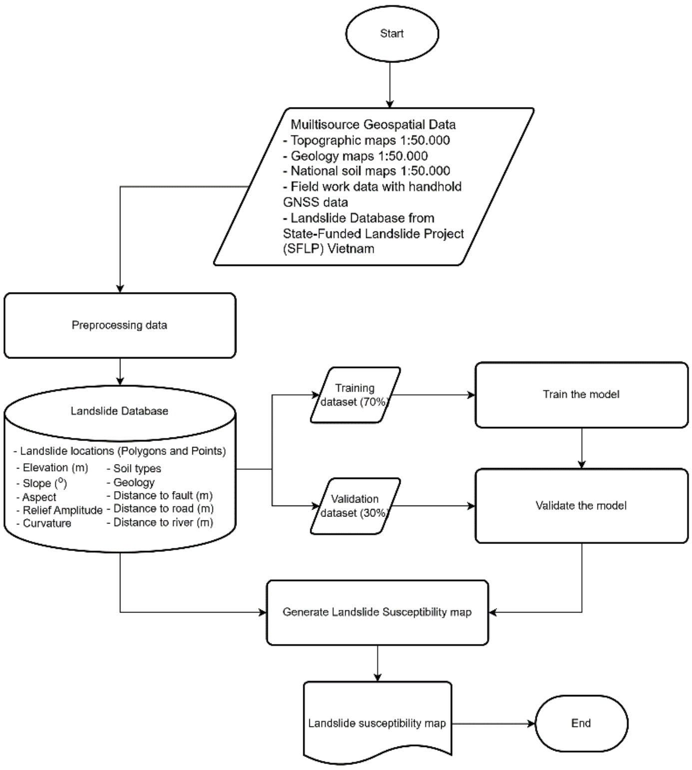

Figure 4. The flowchart of the proposed CNNS-RNNs ensemble model for landslide susceptible mapping

To construct the landslide database, values for the ten influencing factors were extracted for each pixel in the dataset. The database comprises a dependent variable (label) and ten independent variables. Of the independent variables, six were categorical in nature: aspect, soil type, geology, distance to road, distance to river, and distance to fault. The remaining four independent variables were continuous: elevation, slope, curvature, and relief amplitude.

2) Evaluation of Performance

Assessing model performance is crucial for ensuring accuracy and generalizability [30, 31, 32]. We evaluated our model using both training and validation datasets. The training set measures data fitting, while the validation set assesses predictive power.

We employed multiple metrics to evaluate the landslide model's classification ability, including the receiver operating characteristic (ROC) curve and the area under the ROC curve (AUC). These metrics provide an overall measure of predictive accuracy and allow for model comparisons, reflecting specificity and sensitivity.

For this binary classification problem (landslide vs. non-landslide) [33], we calculated the following metrics: True Positive (TP), False Negative (FN), True Negative (TN), and False Positive (FP) [33]. Additional metrics included Positive Predictive Value (PPV), Negative Predictive Value (NPV), Sensitivity (True Positive Rate, TPR), Specificity (Spe), False Positive Rate (FPR), Accuracy (Acc), F1 Score, and Cohen's Kappa Coefficient [33]. These metrics helped identify the best-performing model.

The ROC curve graphically represents classifier performance across different thresholds, plotting FPR on the x-axis and TPR on the y-axis [33]. The AUC measures performance across thresholds, with values ranging from 0.5 (poor) to 1.0 (excellent) [33]. In landslide modeling, AUC is a standard technique for evaluating overall model performance. According to Peterson et al. [34], AUC values between 0.5 and 0.6 indicate very poor performance, 0.6 to 0.7 poor, 0.7 to 0.8 moderate, 0.8 to 0.9 good, and 0.9 to 1.0 very good performance. Thus, AUC serves as a valuable indicator of predictive accuracy, helping to optimize classification thresholds.

3) Benchmark Models and Comparison

To demonstrate the efficacy of the proposed landslide susceptibility model, we compared its performance to that of benchmark classification algorithms. The following benchmark models were considered: Convolutional Neural Networks (CNNs) [22], Recurrent Neural Networks (RNNs) [23], Multi-Layer Perceptron Neural Network (MLPNeuNet) [24], and the BBO-DE Optimized SPAARCTree [25].

The proposed model and each benchmark model were trained and tested using the same train-test split of the dataset. Their performances were evaluated and compared using the AUC metric and Accuracy (Acc), with a higher AUC and Acc indicating better prediction accuracy.

IV. RESULTS AND ANALYSIS

A. *The importance score of the Landslide Influencing Factors*

To ascertain the contribution of the ten landslide influencing factors to the CNNsRNNs model and BBO-DE Optimized SPAARCTree model [25], we applied the wrapper algorithm [35], utilizing five-fold cross-validation to avoid potential bias [36]. Our analysis revealed that slope had the greatest role (score value = 0.299), followed by distance to road (score value = 0.224) and elevation (score value = 0.142). The remaining factors made a lower contribution to the two models, with score values ranging from 0.026 (distance to river) to 0.084 (distance to fault). This outcome closely aligns with the findings from our previous research [25].

B. **Models' Results and Assessment**

The four landslide susceptibility models: Convolutional Neural Networks (CNNs) [22], Recurrent Neural Networks (RNNs) [23], Multi-Layer Perceptron Neural Network (MLPNeuNet) [24], and the BBO-DE Optimized SPAARCTree [25], were successfully trained using the training dataset with ten-fold cross-validation.

Table 1 shows the results of training the five landslide susceptibility models using the training dataset and ten-fold cross-validation to mitigate the risk of overfitting. All models performed well with the training data, but the BBO-DE-STreeEns (AUC = 0.987, Kappa = 0.875, Fscore = 0.939, and Acc = 93.8) and CNNs-RNNs (AUC = 0.991, Kappa = 0.9, Fscore = 0.951, and Acc = 95) models achieved the best performance. In terms of performance, the CNNs and MLPNeuNet exhibited comparable results, while the RNNs achieved slightly better outcomes, as shown in Table 1.

Table 1. Performance metrics of the proposed CNNs-RNNs model and the benchmarks on the training dataset.

Model	Performance Metrics										
	TP	TN	FN	FP	PPV (%)	NPV (%)	Sen (%)	Spe (%)	Acc (%)	Fscore	Kappa	AUC
CNNs-RNNs	77	75	3	5	93.9	96.2	96.3	93.8	95.0	0.951	0.9	0.991
CNNs	64	65	15	16	81.0	80.2	80.0	81.3	80.6	0.805	0.613	0.885
RNNs	76	64	16	4	82.6	94.1	95.0	80.0	87.5	0.884	0.750	0.968
MLPNeuNet	61	63	19	17	78.2	76.8	76.3	78.8	77.5	0.772	0.550	0.859
BBO-DE-STreeEns	77	73	3	7	91.7	96.3	96.1	91.3	93.8	0.939	0.875	0.987

Evaluating the predictive performance of landslide models is crucial for assessing their effectiveness. Using the validation dataset, we found varying levels of performance among the five models (Table 2). The BBO-DE-STreeEns model (AUC=0.940, Kappa=0.735, F-score=0.862, Acc=86.8%) and the CNNs-RNNs model (AUC=0.968, Kappa=0.765, F-score=0.875, Acc=88.2%) exhibited the highest predictive abilities, with excellent statistical metrics. The RNNs model (AUC=0.855, Kappa=0.559, F-score=0.727, Acc=77.9%) also performed well but was slightly less effective. The CNNs model (AUC=0.798, Kappa=0.382, F-score=0.687, Acc=69.1%) and the MLPNeuNet model (AUC=0.748, Kappa=0.294, F-score=0.684, Acc=64.7%) showed satisfactory but lower predictive power.

Table 2. Performance metrics of the proposed CNNs-RNNs model and the benchmarks on the validating dataset.

Model	Performance Metrics										
	TP	TN	FN	FP	PPV (%)	NPV (%)	Sen (%)	Spe (%)	Acc (%)	Fscore	Kappa	AUC
CNNs-RNNs	28	32	6	2	93.3	84.2	82.3	94.1	88.2	0.875	0.765	0.968
CNNs	23	24	10	11	69.7	68.6	67.6	70.5	69.1	0.687	0.382	0.798
RNNs	20	33	1	14	95.2	70.2	58.8	97.1	77.9	0.727	0.559	0.855
MLPNeuNet	26	18	8	16	61.9	69.2	76.5	52.9	64.7	0.684	0.294	0.748
BBO-DE-STreeEns	28	31	6	3	90.3	83.8	82.4	91.2	86.8	0.862	0.735	0.940

The final landslide susceptibility map for Than Uyen district, based on the CNNs-RNNs model, is presented in Figure 5.

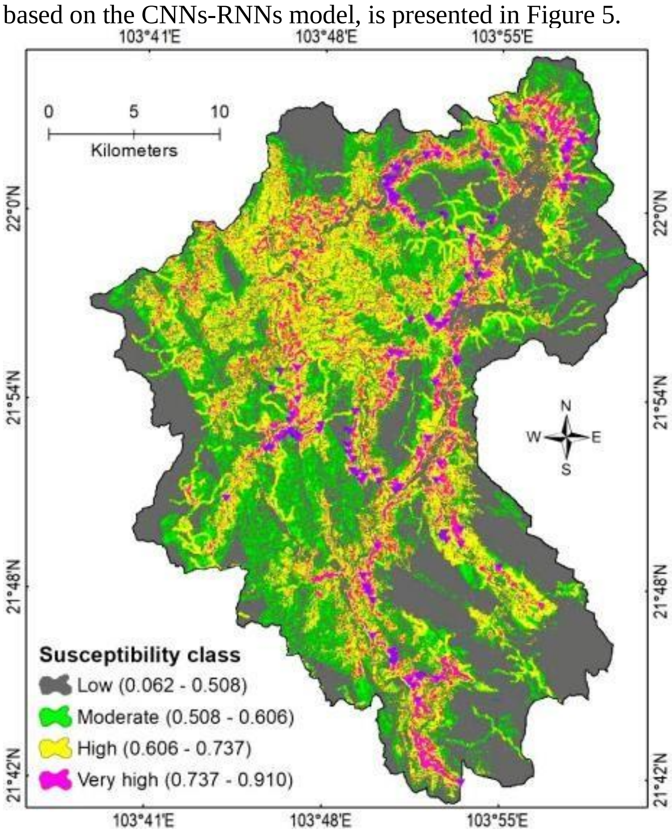

Figure 5. The landslide susceptibility map for Than Uyen district using CNNs-RNNs model.

V. DISCUSSION

Landslides are a significant natural hazard, causing substantial human and economic losses, worsened by improper land use and climate change. Accurate prediction models are essential for mitigating these issues. We developed and validated an ensemble machine learning model, CNNs-RNNs, for landslide susceptibility mapping in Than Uyen district, Vietnam, a region prone to landslides and floods.

Our CNNs-RNNs model combines the strengths of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) networks, optimized using the Adam algorithm. CNNs excel in spatial data analysis, while LSTMs manage temporal data like weather conditions. The model's excellent predictive power confirms its effectiveness.

This model outperformed benchmarks from our previous research, including CNNs, RNNs, MLPNeuNet, and BBO-DE-STreeEns [25]. Among the ten landslide factors, slope and proximity to roads were the most significant, which is reasonable given Than Uyen's mountainous terrain. Landslides mainly occur on slopes between 16 and 34 degrees, often near roads.

However, the distribution of landslide samples along roads could introduce bias, affecting model accuracy. To mitigate this, we used multi-source data, including field surveys, remote sensing, and historical records. We also employed random effect variables, sensitivity analysis, and both non-spatial and spatial cross-validation techniques.

While rainfall is a known factor in landslide modeling, we couldn't incorporate it due to a lack of accurate data. Future research should include rainfall and address uncertainties in its predictions.

VI. CONCLUSIONS

This research introduced a novel ensemble machine learning model, CNNs-RNNs, for landslide susceptibility mapping, validated against a Than Uyen district database comprising 114 landslide and 114 non-landslide locations, and ten influential factors. The model's performance was also compared with four benchmark models: CNNs [22], RNNs [23], MLPNeuNet [24], and the BBO-DE-STreeEns [25]. Our study led to the following significant conclusions:

The integration of CNNs and RNNs (LSTM networks) with the Adam Optimizer resulted in a robust ensemble model, offering precise landslide susceptibility mapping.

The CNNs-RNNs model outperformed benchmark models, underscoring its potential for highly accurate landslide susceptibility mapping.

Ten influential landslide factors including elevation, slope, curvature, aspect, relief amplitude, soil type, geology, distance to faults, distance to roads, and distance to rivers, were identified based on landslide inventory analysis and the study area's geoenvironmental characteristics. Each factor scored an importance value greater than zero, confirming their significance in predicting landslide occurrences.

Of all factors considered, the slope and distance to roads were the most significant contributors to landslides in Than Uyen district.

The result of this study offers critical insights for Than Uyen district authorities and policymakers, assisting in informed land-use planning and territorial management decisions.

VII. REFERENCES

[1] Petrucci, O.: Landslide fatality occurrence: a systematic review of research published between January 2010 and March 2022. Sustainability 14(15), 9346 (2022). https://doi.org/10.3390/su14159346

[2] Sim, K.B., Lee, M.L., Wong, S.Y.: A review of landslide acceptable risk and tolerable risk. Geoenvironmental Disasters 9(1), 3 (2022). https://doi.org/10.1186/s40677-02200205-6

[3] Thirugnanam, H., et al.: Review of landslide monitoring techniques with IoT integration opportunities. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 15, 5317–5338 (2022)

[4] Araújo, J., et al.: Impact of extreme rainfall events on landslide activity in Portugal under climate change scenarios. Landslides 19(10), 2279–2293 (2022)

[5] Lin, Q., et al.: Evaluation of potential changes in landslide susceptibility and landslide occurrence frequency in China under climate change. Science of the total environment 850, 158049 (2022)

[6] Bozzolan, E., et al.: A mechanistic approach to include climate change and unplanned urban sprawl in landslide susceptibility maps. Science of the total environment 858, 159412 (2023)

[7] He, Q., et al.: Landslide and Wildfire Susceptibility Assessment in Southeast Asia Using Ensemble Machine Learning Methods. Remote Sensing 13(8), 1572 (2021)

[8] Liu, L.-L., et al.: A bibliometric analysis of the landslide susceptibility research (1999– 2021). Geocarto International (2022)

[9] Liu, S., Wang, L., Zhang, W., He, Y., Pijush, S.: A comprehensive review of machine learning-based methods in landslide susceptibility mapping. Geological Journal (2023)

[10] Merghadi, A., et al.: Machine learning methods for landslide susceptibility studies: A comparative overview of algorithm performance. Earth Science Reviews 207, 103225 (2020)

[11] Martínez-Álvarez, F., Bui, D.T.: Advanced Machine Learning and Big Data Analytics in Remote Sensing for Natural Hazards Management. Remote Sensing 12(2), 301 (2020)

[12] Yaghoubzadeh-Bavandpour, A., et al.: Deep Learning Application in Water and Environmental Sciences. In: Computational Intelligence for Water and Environmental Sciences. Springer, Singapore (2022), pp. 273–290

[13] Pourghasemi, H., et al.: Landslide susceptibility assessment and mapping using state of the art machine learning techniques. Nat Hazards 108, 1291–1316 (2021)

[14] Hong, H.: Assessing landslide susceptibility based on hybrid Best first decision tree with ensemble learning model. Ecological Indicators 147, 109968 (2023)

[15] Gundersen, O., et al.: Do machine learning platforms provide out-of-the-box reproducibility?. Future Generation Computer Systems 126, 34-47 (2022)

[16] Zenodo: TensorFlow. Available at: https://zenodo.org/record/8118033 (last accessed 2023/07/15)

[17] Kavzoglu, T., Colkesen, I., Sahin, E.K.: Machine learning techniques in landslide susceptibil-ity mapping: A survey and a case study. In: Landslides: Theory, Practice and Modelling. Springer, Berlin/Heidelberg (2019), pp. 283–301

[18] Pourghasemi, H.R., Pouyan, S., Bordbar, M., Golkar, F., Clague, J.J.: Flood, landslides, forest fire, and earthquake susceptibility maps using machine learning techniques and their combination. Natural Hazards 116, 3797–3816 (2023). https://doi.org/10.1007/s11069023-06072-0

[19] Youssef, A.M., Mahdi, A.M., Pourghasemi, H.R.: Landslides and flood multi-hazard assessment using machine learning techniques. Bulletin of Engi-neering Geology and the Environment 81, 1–23 (2022). https://link.springer.com/article/10.1007/s10064-02202874-x

[20] Fang, Z., Wang, Y., Peng,20. Fang, Z., Wang, Y., Peng, L.: A comprehensive review of landslide susceptibility mapping using machine learning and deep learning models. Earth Systems and Environment 5(2), 383-405 (2021). https://doi.org/10.1080/13658816.2020.1808897

[21] Kundu, R., Das, R., Geem, Z.W., Han, G.-T., Sarkar, R.: Pneumonia detection in chest Xray images using an ensemble of deep learning models. PLoS ONE 16(9) (2021). https://doi.org/10.1371/journal.pone.0256630

[22] Krizhevsky, A., Sutskever, I., Hinton, G.E.: ImageNet classification with deep convolutional neural networks. In: Advances in Neural Information Processing Systems, pp. 1097– 1105 (2012)

[23] Hochreiter, S., Schmidhuber, J.: Long short-term memory. Neural computation 9(8), 1735–1780 (1997). doi: 10.1162/neco.1997.9.8.1735

[24] Delashmit, W.H., Manry, M.T.: Recent developments in multilayer perceptron neural networks. In: Proceedings of the seventh annual memphis area engineering and science conference, MAESC (2005)

[25] Hoang, D.A., Le, H.V., Pham, D.V., Hoa, P.V., Tien Bui, D.: Hybrid BBO-DE Optimized SPAARCTree Ensemble for Landslide Susceptibility Mapping. Remote Sens. 15, 2187 (2023). https://doi.org/10.3390/rs15082187

[26] Kingma, D.P., Ba, J.: Adam: A method for stochastic optimization. In: International Conference on Learning Representations (ICLR) (2015). https://arxiv.org/abs/1412.6980

[27] Hung, L.Q., Van, N.T.H., Van Son, P., Ninh, N.H., Tam, N., Huyen, N.T.: Landslide inventory mapping in the fourteen Northern provinces of Vietnam: Achievements and difficulties. In: Advancing Culture of Living with Landslides; ISDR-ICL Sendai Partnerships 2015–2025. Springer: Berlin/Heidelberg, Germany, 1, pp. 501–510 (2017). https://doi.org/10.1007/978-3-319-59469-9_44 General Statistic Office: Statistical Yearbook of Vietnam. General Statistic Office, Hanoi, Vietnam (2019)

[28] Vietnam Institute of Geosciences and Mineral Resources. Landslide Warning Website. Available online: http://www.canhbaotruotlo.vn/hientrangcactinh.html (accessed on 8 December 2021).

[29] Le, H.V., Bui, Q.T., Bui, D.T., Tran, H.H., Hoang, N.D.: A Hybrid Intelligence System Based on Relevance Vector Machines and Imperialist Competitive Optimization for Modelling Forest Fire Danger Using GIS. Journal of Environmental Informatics 36(1) (2020).

[30] Le, H.V., Hoang, D.A., Tran, C.T., Nguyen, P.Q., Hoang, N.D., Amiri, M., Ngo, T.P.T., Nhu, H.V., Van Hoang, T., Tien Bui, D.: A new approach of deep neural computing for spatial prediction of wildfire danger at tropical climate areas. Ecological Informatics 63, 101300 (2021). https://doi.org/10.1016/j.ecoinf.2021.101300

[31] Bui, D.T., Le, H.V., Hoang, N.-D.: GIS-based spatial prediction of tropical forest fire danger using a new hybrid machine learning method. Ecological Informatics 48, 104–116 (2018). https://doi.org/10.1016/j.ecoinf.2018.08.008

[32] Powers, D.M.: Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation. arXiv preprint arXiv:2010.16061 (2020).

[33] Peterson, A.T., Papeş, M., Soberón, J.: Rethinking receiver operating characteristic analysis applications in ecological niche modeling. Ecological modelling 213(1), 63-72 (2008). https://doi.org/10.1016/j.ecolmodel.2007.11.008

[34] Kohavi, R., John, G.H.: Wrappers for feature subset selection. Artificial intelligence 97(12), 273–324 (1997).

[35] Nhu, V.-H., et al.: An approach based on socio-politically optimized neural computing network for predicting shallow landslide susceptibility at tropical areas.