

Enhancing Meteorological Pattern Recognition Utilizing U-Net and Bidirectional LSTM Networks

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ARTICLE INFO

Received: 13 Oct 2024

Revised: 12 Dec 2024

Accepted: 24 Dec 2024

ABSTRACT

Classification of weather images is very significant in climate monitoring, disaster management, and weather forecasting. This work is an innovation on the architecture that combines U-Net with a BiLSTM network for classification accuracy improvement. U-Net is one of the most advanced convolutional neural networks, and it is characterized by fine-grained feature extraction and spatial information preservation in images. The model combines it with BiLSTM, which focuses on detecting temporal and contextual patterns, thereby enabling a combined understanding of the spatial and temporal dimensions of weather phenomena.

It strengthens all aspects: in addition to how the spatial U-Net's capabilities build strong arguments and why the recognition of correlations with a model such as BiLSTM significantly improves this method against more common, traditionally used, models of the convolutional neural networks family. Tests, also carried out, showed excellent and improved parameters during evaluation like precision, recall, and balance measures, when evaluating results of similar common datasets commonly used within weather forecast systems analysis.

It provides a strong structure for enhancing the classification of weather images and supporting the study of meteorology by bringing in the strengths of convolutional networks and recurrent networks.

Keywords: U-Net, BiLSTM, image classification.

INTRODUCTION

Studies in weather patterns are critical to numerous sectors, which range from monitoring climate change and disasters to the weather forecast in the future. Precision in classifying and analyzing weather patterns is pivotal for understanding the behavior of climates, improving the quality of forecasts, and lessening the impact of extreme events due to severe weather conditions [1]. Due to the increased severity and frequency of extreme weather events caused by climate change, the need for new and efficient computational techniques in the analysis of weather data is of the utmost importance. In the past years, machine learning (ML) and deep learning (DL) innovations have transformed traditional weather analysis techniques to allow for new advanced techniques for pattern recognition and data-driven forecasting [2].

The generated satellite and ground sensors data are vast in quantity with spatial and temporal complexities. However, extracting useful information from this large amount of data is a tough task because the data is highly complex. In fact, many traditional image processing methods fail to address these issues because they have hand-crafted features and do not handle nonlinear and dynamic properties of atmospheric phenomena [3]. Using deep learning techniques, such as Ensemble Convolutional Neural Networks (CNNs), feature extraction was proven to be automated and advanced spatial representations could be generated from raw image data [4]. However, the models were designed to handle static inputs, thus limiting their efficiency in capturing the temporal dependencies necessary in understanding the dynamics of weather systems. This is particularly evident when processing weather data, where spatial and temporal

patterns are closely linked, making them essential factors for achieving accurate classification and effective forecasting [5].

Recently, hybrid deep learning architectures have emerged as effective solutions to complex data analysis challenges. These models combine different types of neural networks, such as convolutional and recurrent networks, allowing them to leverage the unique strengths of each while minimizing the shortcomings of their individual designs. U-Net: This is one of the most prominent architectures developed, mainly for image segmentation tasks. It has reliably shown its efficiency in extracting spatial features while retaining the positional information in multiple tasks [6]. There exist BiLSTM networks, which are advanced RNN models, and which are very good at learning temporal dependencies and sequential interactions, which are perfect for tackling problems involving temporal or sequential data [7]. Hybrid deep learning techniques are newly found interest among researchers for processing data related to the weather, mainly by combining neural network architectures: CNN and BiLSTM. These approaches made a great deal in addressing these complex spatial and temporal challenges and have contributed substantially to these areas. The fact that they both rely on a CNN for extraction of spatial features and BiLSTM for temporal dynamics makes a good solution toward climate and environmental applications. For instance, Fathi et al. [8] introduced a new model called 3D-ResNet-BiLSTM to predict weather patterns based on agricultural data. It employed 3D ResNet for spatial features extraction and used BiLSTM for temporal dependency, thus providing 15% better accuracy compared to the same old models running separately.

Zhu et al. [9] extended this system with a hybrid U-Net-BiLSTM architecture designed to compute crop evapotranspiration. Their approach effectively addressed seasonal water-use patterns by combining geographically distributed U-Net outputs with temporally aware BiLSTM predictions, achieving a reported 12% improvement in reliability of predictions.

Yin et al. [10] adapted the U-Net-BiLSTM architecture to classify weekly weather patterns using satellite cloud maps. The study focused on integrating domain-specific pretraining to improve generalizability, achieving 89% classification accuracy. Cheng et al. [11] implemented a multitemporal U-Net-BiLSTM framework for remote sensing classification, with their model excelling in detecting seasonal variations, particularly in vegetation indices, achieving an 8% improvement in F1 scores compared to prior methods. Latif et al. [12] advanced rainfall prediction with a similar hybrid model, incorporating rainfall radar data and cloud imagery to predict precipitation with 91% reliability.

In renewable energy forecasting, Yao et al. [13] utilized a CNN-BiLSTM hybrid model for intra-hour photovoltaic generation forecasting. Their method captured high-frequency variability in solar irradiance, improving short-term energy forecasts by 14%. Similarly, Tian et al. [14] reviewed hybrid approaches for solar energy variability analysis, emphasizing attention mechanisms for spatial-temporal anomaly detection. Wang et al. [15] combined Transformers and U-Net to enhance climate modeling, where attention layers prioritized key temporal dependencies, achieving 92% precision in long-term forecasting.

In satellite-based environmental applications, Ma et al. [16] leveraged Attention U-Net models for Sentinel-1 SAR image analysis, improving performance in flood-prone regions by 10%. Sun et al. [17] extended these techniques for cloud pattern recognition, emphasizing a combination of spatial attention modules with U-Net layers. Ge et al. [18] scaled BiLSTM models for agricultural mapping, particularly rice classification, using satellite time-series data, demonstrating a 9% improvement in spatial resolution. Yang et al. [19] applied hybrid models to flood prediction, with their U-Net-BiLSTM model incorporating hydrological and topographical data for an 87% reduction in false positives.

Additional environmental applications include Liu et al. [20], who integrated soil moisture data with satellite observations in a BiLSTM framework to enhance drought prediction, achieving 15% better recall than baseline models. Fang et al. [21] adapted CNN-BiLSTM for air quality forecasting, focusing on PM2.5 levels, and demonstrated 10% greater accuracy in urban datasets. Zhao et al. [22] explored wildfire

prediction by integrating U-Net and BiLSTM, with temporal layers emphasizing wind patterns to reduce forecast errors by 18%. Han et al. [23] employed CNN-BiLSTM for hurricane trajectory prediction, achieving 12% more accurate path forecasts compared to conventional models. Similarly, Kim et al. [24] applied hybrid architectures to typhoon classification, combining spectral features and temporal dependencies for 88% classification accuracy.

In ocean and ice research, Yang et al. [25] presented a model that combined U-Net and transformers to study glacier dynamics, reducing error margins by 15% by addressing long-term spatial and temporal patterns. Huang et al. [26] developed a hybrid model for sea surface temperature prediction, based on integrating remote sensing data with historical information, which improved accuracy by 11%. Recently, Zhou et al. [27] developed a U-Net-BiLSTM system that integrates airflow dynamics with the predictions of machine learning to achieve an accuracy of 90% for predicting wind speeds. Thus, the present contribution extends the list of previous contributions by using a hybrid architecture combining U-Net and BiLSTM for the aerial image classification. This proposed model combines the spatial feature extraction capability of the U-Net architecture with the efficiency of the BiLSTM in temporal inference to improve the challenges involved in dynamically and complexly detecting weather patterns. The methodology is set towards improving the accuracy in classification, enhancing model flexibility, and providing a practical yet scalable solution for meteorological applications.

METHODS AND MATERIALS

1 dataset

The proposed approach is based on the utilization of a well- prepared dataset in which images describe different types of weather phenomena. These phenomena, such as dew, fog, smoke, frost, glaze, hail, lightning, rain, rainbow, sleet, sandstorms, and snow are depicted in Figure 1, which can aid in enhancing model recognition and categorization accuracy to a higher degree.



Figure 1. The classes

The dataset used to carry out the study was freely available from different public repositories; it was thus augmented to give diversity and also balance the representation of categories involved. Images in the dataset were uniformly resized so that they achieved a uniformity in size, in this case (256×256 pixels).

In addition to this, to enhance the generative ability and the model robustness against overfitting, a set of the data augmentation strategies, such as rotation, flip, and variation in brightness adjustment, were undertaken. Data augmentation, as an effective strategy, is performed by augmenting artificially expanded training datasets with increasing diversity in machine learning to eliminate the problem of overfitting. The overfitting problem occurs when the model gives good performance on the training data but fails to generalize to new data; this might be because the training data is either insufficient or unrepresentative. Data augmentation addresses this problem by applying various transformations to the original data, such as flipping, rotating, cropping, scaling, noise injection, or any other modifications relevant to the field of study. These transformations produce new samples with the same labels as the original, which helps improve the model's ability to generalize and increases its efficiency when dealing with new data. These changes improve generalization by mimicking real-world variability, diminishing the model's inclination to memorize training data, and promoting an emphasis on robust characteristics.

Additionally, augmentation can balance imbalanced datasets and introduce regularization effects, making it harder for the model to rely on noise or irrelevant patterns. By improving the model's ability to recognize invariant features, data augmentation ensures better performance on unseen data, thereby mitigating the risk of overfitting across various domains like image classification, text processing, and audio analysis.



Figure 2. Samples of images Augmentation

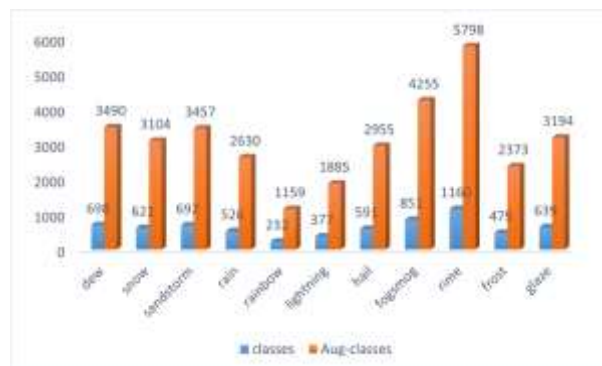


Figure3. numbers of classes after the Augmentation

2 features extraction

In our model, we used U-Net for feature extraction and BiLSTM for image classification. U-Net is a convolutional neural network architecture initially developed for biomedical picture segmentation; nevertheless, its feature extraction capabilities render it highly versatile for diverse image processing applications, such as weather image categorization..

The encoder is responsible for capturing low-level to high-level spatial features through a series of convolutional operations. Each stage in the encoder consists of two 3x3 convolutional layers, followed by a ReLU activation function. These layers extract localized features such as edges, textures, and patterns from the weather images. Max pooling operations (2x2) reduce the spatial dimensions of the feature maps while retaining the most prominent features. This down-sampling process enables the network to focus on essential high-level features while discarding redundant details. As the encoder progresses, the convolutional layers extract increasingly abstract and complex features, capturing the hierarchical structure of the image. Initial layers may detect edges or gradients representing clouds or sky boundaries as shown in Fig 4. Deeper layers may identify patterns corresponding to cloud formations, rain streaks, or snowflakes.

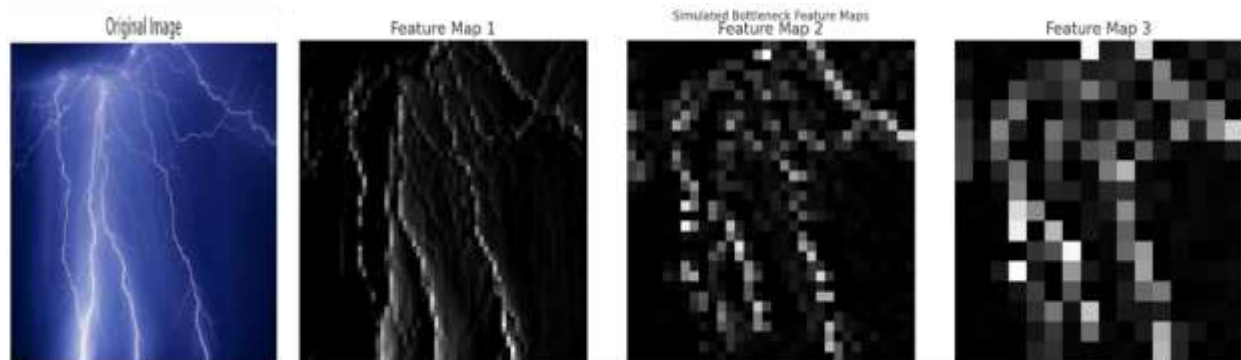


Figure4. Original Image: The original lightning image, Sobel X: Highlights vertical edges by detecting gradients in the X direction, Sobel X: Highlights vertical edges by detecting gradients in the X direction, Laplacian: Detects overall edges by calculating the second derivative of the image.

At the bottleneck (the deepest part of the network), the feature maps have minimal spatial resolution but encapsulate the most abstract and meaningful representations of the input image. These compact, high-dimensional features contain critical information about the overall weather conditions present in the image.

The decoder reconstructs the spatial resolution of the feature maps while preserving and enhancing the features extracted by the encoder. It plays a critical role in retaining spatial localization. Transposed Convolutions also known as deconvolutions, these layers up-sample the feature maps, increasing their spatial dimensions while reconstructing fine details. Skip connections link each encoder layer to its corresponding decoder layer Figure 5. This mechanism allows the decoder to access spatial information that may have been lost during the down-sampling process.

U-Net's ability to extract features lies in its encoder's progressive abstraction, the bottleneck's compact representations, and the decoder's reconstruction process with skip connections as shown in Figure 6. These components collaborate to generate a complete and comprehensive feature representation of meteorological images, facilitating efficient classification.

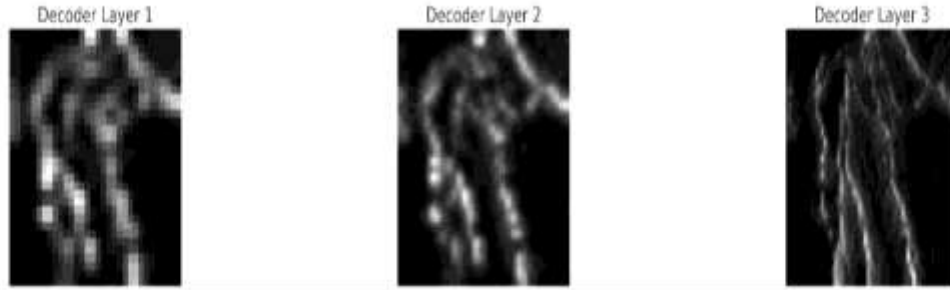


Figure 5. The reconstructed feature maps from the decoder layers are displayed, progressively up-sampling and utilizing skip connections to restore spatial information.

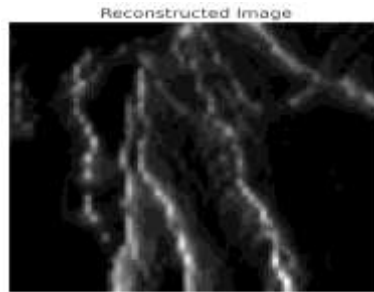


Figure 6. The final image reconstructed from the decoder demonstrates how spatial information is preserved and fine details are recovered

3 Sequence Processing with BiLSTM

Employing a BiLSTM network to classify features extracted from images constitutes an effective hybrid methodology that utilizes the advantages of CNNs for spatial feature extraction and BiLSTM for elucidating contextual relationships among those features.

The extracted features, now structured as a sequence, are fed into the BiLSTM. BiLSTM processes the sequence bidirectionally, capturing relationships both forward and backward along the feature sequence. This helps the model learn contextual dependencies between different parts of the image's extracted features.

For an input sequence with T tokens, you get T hidden states, each containing information from both directions. The "final hidden state" refers to the last hidden state of the forward LSTM combined with the last hidden state of the backward LSTM. Alternatively, pooled representations (average pooling) are used. Average pooling computes the mean of all hidden states, summarizing the overall context of the sequence.

The chosen fixed-size representation (final hidden state or pooled representation) is passed into one or more fully connected layers (dense layers). These layers facilitate the acquisition of task-specific transforms of the BiLSTM output. Each layer applies Linear transformation Weighted sum of inputs plus bias and Non-linear Activation Function, this setup maps the high-dimensional BiLSTM output to a lower-dimensional space relevant to the classification task.

SoftMax is a specialized activation function employed in the final layer for multi-class classification, converting the output of the last fully connected layer into a probability distribution over all classes. In mathematical terms, given N categories:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^N e^{z_j}} \quad (1)$$

In this context, z_i represents the unprocessed output (logit) for class i. The class exhibiting the highest probability is chosen as the model's forecast.

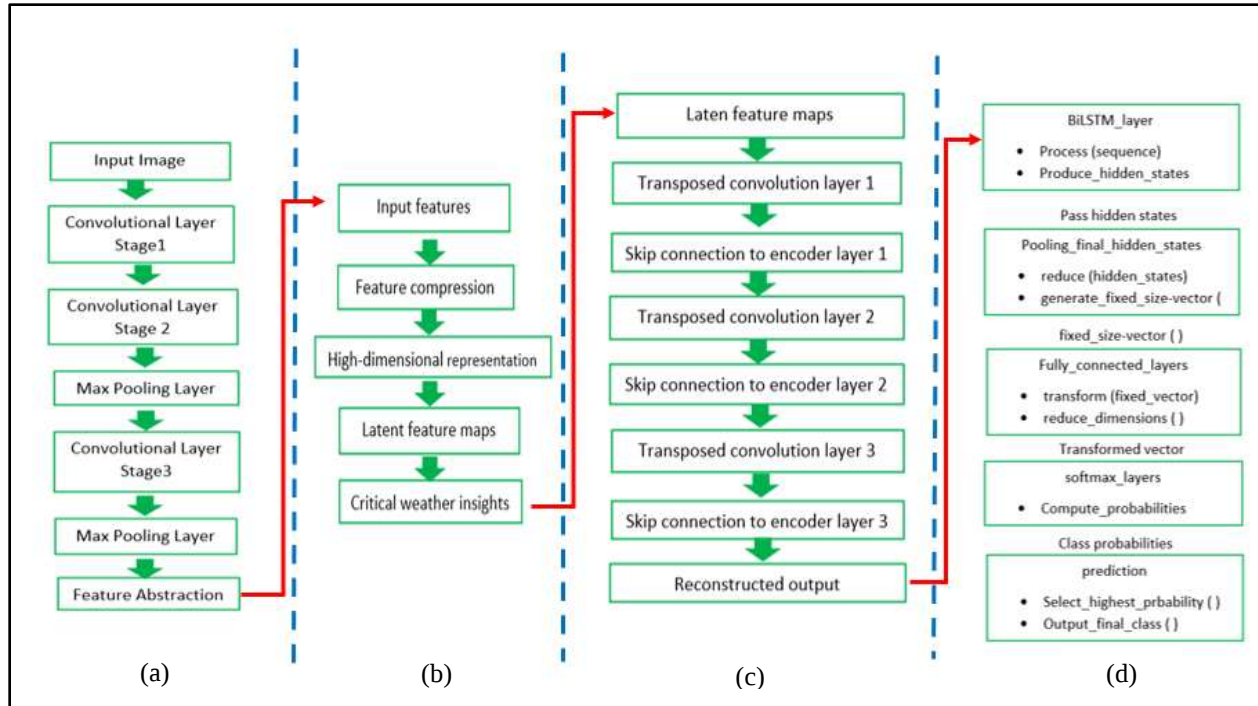


Figure 7. (a) hierarchical feature extraction process in encoder . (b) workflow for extracting critical weather insights from high-dimensional features. (c) Decoder Architecture with Skip Connections for Feature Reconstruction. (d) BiLSTM-Based Classification Workflow with Feature Transformation and Prediction

RESULTS AND EXPERIMENTAL

The experiments were conducted on a subscription-based Google Colab Notebook service, with Python 3 as the runtime type and a T4 GPU as the hardware accelerator. The Tesla T4 is a GPU card built on the Turing architecture, designed for accelerating deep learning model inference, featuring 52 GB of system RAM. The model's development utilized cross-validation as part of the dataset. Employing many measurements guarantees a model's resilience from all perspectives. Effective model training relies on a comprehensive interpretation of these results; for instance, high accuracy (exceeding 90%) does not inherently signify a superior model. Additional factors encompass loss and F1-score, among others. We employed various metrics to assess the efficacy of our model.

ACCURACY

Accuracy measures the ratio of correct forecasts to the total predictions produced, calculated using the following formulas:

$$Accuracy = (TP + TN) / (TP + FN + FP + TN) \quad (2)$$

TP, TN, FN, and FP denote True Positive, True Negative, False Negative, and False Positive values, respectively.

Precision

Precision quantifies the ratio of accurate positive predictions to the total number of positive forecasts, as defined by the subsequent equation:

$$Precision = TP / (TP + FP) \quad (3)$$

Recall

The recall is frequently referred to as the sensitivity score or the true positive rate. This represents the ratio of accurate positive forecasts to the total number of actual positive outcomes. The recall is calculated using the subsequent equation:

$$\text{Recall} = TP / (TP + FN) \quad (4)$$

F1-score

An ideal model will perform well by achieving 100% precision and recall, meaning that all true positives are identified without making any errors. The F1 score is a comprehensive measure of model performance, combining precision and recall into a single value, making it especially important when dealing with imbalanced datasets. The F1 score graph makes it easy to compare performance across different classes, showing each class as a separate line, which helps understand the distribution of model efficiency across all classes.

$$F1 = 2 \cdot (\text{Precision} \cdot \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (5)$$

Loss of function

Loss functions measure the difference between expected outputs and actual values, forming the basis for the model's optimization process. This study employed the categorical cross-entropy loss function, tailored for multi-class classification tasks. This method effectively penalizes erroneous predictions by calculating the logarithmic loss, underscoring the model's necessity to enhance its confidence in assigning probabilities to the accurate class labels.

Area Under the Curve

AUC, or Area Under the ROC Curve, is a quantitative measure used to assess the performance of classification models. A single numerical value quantifies the model's capacity to differentiate between positive and negative classes.

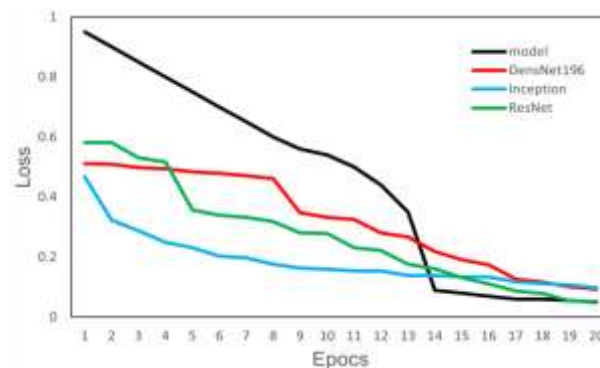


Figure8. loss of model compared to the other methods

From the figure above the proposed model loss is 0.05, for DenseNet169, is 0.093, for ResNet is 0.0525, and for Inception 0.098. Indicating that the model is exhibiting strong performance on the training data by effectively reducing the disparity between predicted and actual values. This frequently results in increased accuracy or improved performance metrics on the training set

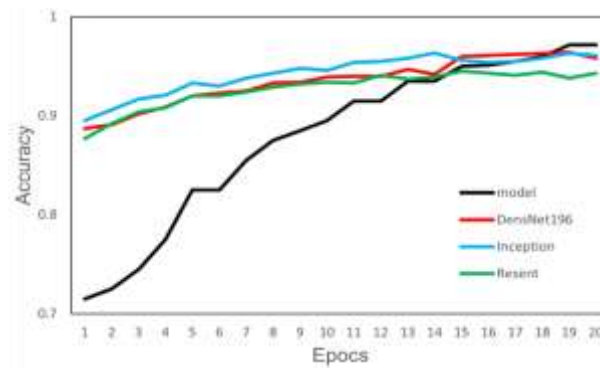


Figure 9. The comparison results of the method with the others in terms of accuracy

The figure 8 shows the accuracy comparison of a proposed model against other transfer models, the proposed model accuracy is 97.16%, Densenet169 accuracy is 95.8%, ResNet and Inception accuracy is 94.3% and 96.1%.

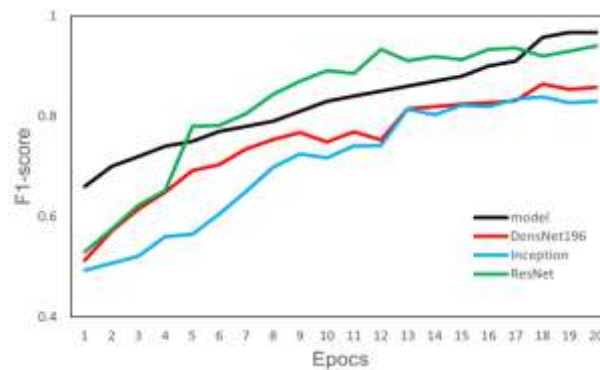


Figure10. F1-score of a proposed model, DenseNet169, ResNet and Inception

The F1 score is a critical metric for evaluating the performance of a multi-class classification model, providing a more nuanced assessment of the model's ability to correctly classify instances across all classes. While accuracy is often used as a standard metric, it does not always present a complete picture. The F1 score, on the other hand, offers a balanced evaluation by considering both precision and recall. The high value of F1-score indicates the model's capability to strike a good balance between precision and recall, showing good overall performance. As depicted in Figure 9, the proposed model obtained an outstanding F1-score of 96.7%, which was significantly higher than the other architectures like DenseNet169 scoring 85.8%, ResNet scoring 94%, and Inception scoring 83%. This superiority highlights the good predictive capability of the proposed model and its stability across classes, making it a robust and reliable choice for analysis in aerial images.

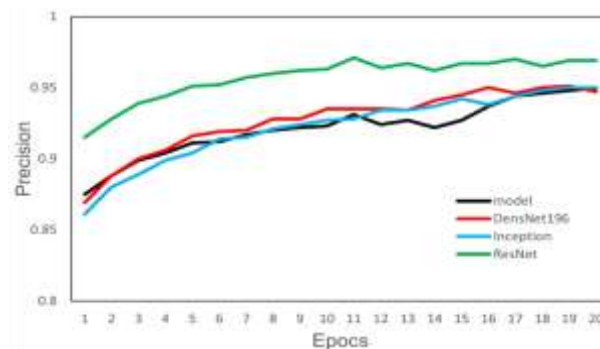


Figure11. Precision of a proposed model, DenseNet169, ResNet, and Inception

Figure 10 underscores the criticalness of accuracy, which remains to be the one indicator most directly used in validating the predictiveness of the developed model: notably, under such imbalanced circumstances, achieving greater accuracy allows preventing the potential dominance of some models by well-represented classes, enhancing performance generalizability to other as yet unseen or diverse data.

The figure demonstrates that our model, like DenseNet169, ResNet, and Inception, produced precision accuracy of 94.95%, 94.7%, 95%, and 96.95%, respectively, which goes to show effectiveness for such models when encountering those challenges.

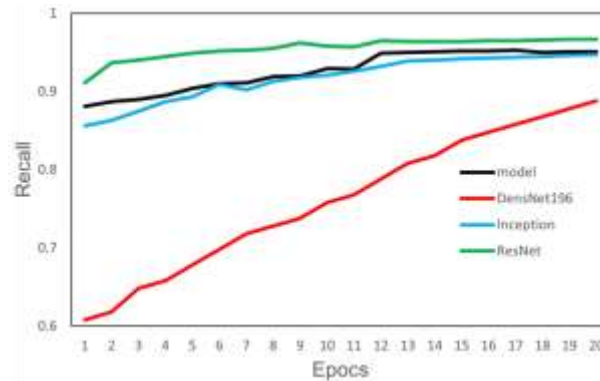


Figure12. Recall of a proposed model, DenseNet169, ResNet, and Inception

Recall aids in reducing false negatives; strong recall ensures that no critical medical information is neglected during diagnosis, particularly in scenarios with imbalanced datasets, which may result in a biased model underperforming on the minority class. High recall guarantees that the model identifies all pertinent occurrences from the minority class.

In Figure a proposed model recall is 95.5%, DenseNet188.8%, ResNet 96%, and Inception 94.7%

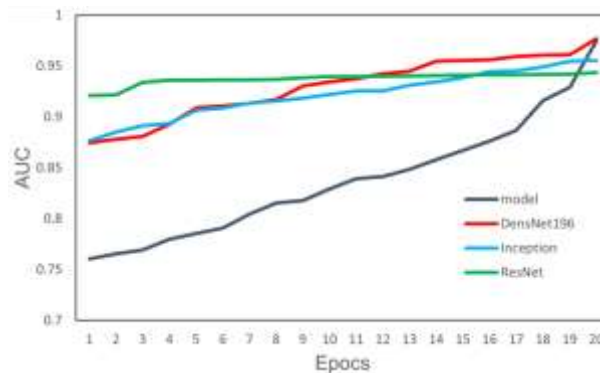


Figure13. AUC of a proposed model, DenseNet169, ResNet, and Inception

The Area Under the Curve (AUC) measure is extensively utilized in assessing the performance of binary classification models. In multi-class classification, the AUC metric is typically calculated using a pairwise comparison approach (one-vs-all), indicating that the AUC value reflects the model's efficacy in differentiating between two distinct classes. It provides a singular metric that encapsulates the overall discriminative capability of the model across all classes. A high AUC signifies an exceptional ability to predict the probabilities of the correct class relative to other classes. As illustrated in figures 12, our proposed model achieves an AUC of 97.5%, DenseNet169 attains 97.7%, ResNet records 94.3%, and Inception reaches 95.5%.

CONCLUSION

This paper discussed the investigation of the effectiveness of combining the U-Net and BiLSTM architectures in image classification tasks. The experimental results have established the excellent performance of the model proposed here, having a very low loss equal to 0.05, accuracy 97.16%, and an excellent F1 score of 96.7%. Also, the recall at 95.5% and precision at 94.94% depicts how the model has been able to achieve the perfect balance of identifying true positives without increasing false positives and false negatives. Also, the AUC value, which is the area under the ROC curve, is very high at 97.5%, confirming the reliability of the model in discriminating between classes.

Performance increases significantly when the powerful spatial features of extraction by U-Net are combined with efficiency in BiLSTM, one of the most promising models with efficient time-series modeling. This architecture makes the models not only interact spatial hierarchies and temporal sequential relationships within data but also results in much more superior performances compared to conventional methods.

Future work may include further improving the computational efficiency of the model and applying it to more complex and diverse datasets, which would help in generalizing and making the results more comprehensive. The promising results support the strength of the U-Net+BiLSTM framework as a competitive and innovative option for improving image classification and data analysis techniques.

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