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TeutongNet: A Fine-Tuned Deep Learning Model for Improved Forest Fire Detection

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Abstract

Forest fires have emerged as a significant threat to the environment, wildlife, and human lives, necessitating the development of effective early detection systems for firefighting and mitigation efforts. In this study, we introduce TeutongNet, a modified ResNet50V2 model designed to detect forest fires accurately. The model is trained on a curated dataset and evaluated using various metrics. Results show that TeutongNet achieves high accuracy (98.68%) with low false positive and false negative rates. The model's performance is further supported by the ROC curve analysis, which indicates a high degree of accuracy in classifying fire and non-fire images. TeutongNet demonstrates its effectiveness in reliable forest fire detection, providing valuable insights for improved fire management strategies.

1. Introduction

Forest fires pose a significant threat to the environment, wildlife, and human lives [1]. Characterized by their uncontrollable spread and fierce intensity, it possesses the capacity to unleash catastrophic consequences upon ecosystems and the environment as a whole. These fires ravage vast expanses of pristine woodlands, consuming invaluable vegetation, destroying essential habitats, and disrupting the intricate web of life that thrives within these ecosystems [2, 3]. The detrimental effects extend beyond the immediate inferno, as the ensuing loss of vegetation can lead to soil erosion, exacerbate the risk of flooding, and result in long-term ecological degradation [4, 5].

For instance, let's consider the case of Australia, a country that has experienced devastating forest fires in recent years. In the summer of 2019-2020, Australia faced one of the most severe wildfire seasons in its history, commonly referred to as the Black Summer [6, 7]. These fires resulted in widespread destruction, impacting millions of hectares of land, countless animal species and tragically claiming numerous lives [8, 9]. By studying the events of the Black Summer, we can identify key lessons to improve our ability to detect and respond to wildfires. Detecting and monitoring forest fires in their early stages is crucial for effective firefighting and mitigating the damages caused [10]. To address the urgent need for early detection methods, researchers and authorities have turned to deep learning, a branch of artificial intelligence that has emerged as a valuable tool in this regard. By leveraging deep learning models, authorities can continuously monitor vulnerable areas, detect fires in their early stages, and provide real-time alerts. Such proactive measures enhance the chances of successful firefighting operations, minimize property damage, and, most importantly, save lives [11].

In recent years, deep learning models have shown great promise in the field of forest fire detection. The integration of deep learning techniques into forest fire detection systems has shown promising results [12–16]. However, while deep learning models have shown great promise in forest fire detection, there is still a need to address cases where the prediction indicates no fire when a fire actually occurs. False prediction can have severe consequences, leading to delayed response and increased damage. Therefore, it is crucial to continuously improve the accuracy and reliability of deep learning models to minimize false prediction.

One such deep learning architecture that has gained popularity is ResNet50V2 [17]. ResNet50V2 is a convolutional neural network that has achieved remarkable performance in image classification tasks [18, 19]. By leveraging its pre-trained weights and features learned from large-scale datasets, we can leverage transfer learning to adapt ResNet50V2 for forest fire detection.

However, achieving optimal performance with ResNet50V2 requires careful fine-tuning of its parameters. Hyperparameter tuning is a crucial step in optimizing the model's architecture, such as adjusting learning rates, batch sizes, and regularization techniques [20]. In addition to fine-tuning, modifying the ResNet50V2 layers can also enhance the model's ability to detect forest fires accurately while minimizing false alarms [21].

In this study, we propose TeutongNet, a modified ResNet50V2 model designed for forest fire detection. Our primary objective was to enhance the accuracy of the model beyond the existing models in this domain. Existing models have made significant contributions in this area, but there is still room for improvement, particularly in terms of accuracy minimizing instances where fire is predicted as no fire. Therefore, our study focuses on developing TeutongNet to address this specific limitation.

The rest of the paper is organized as follows: In Section 2, we present the methodology employed in our study, including the dataset used, the experimental setup, and the evaluation metrics. In Section 3, we present the results and analysis of our experiments. Finally, in Section 4, we summarize our contributions and suggest directions for future research.

2. Materials and Methods

2.1. Dataset

The dataset used in this study is Forest Fire dataset, which was curated specifically for forest fire detection [22]. It consists of 3-channeled images with a resolution of 250 × 250 pixels. The overview of the dataset can be seen in Figure 1. The dataset focuses on the binary problem of fire detection in forest landscapes. It is a balanced dataset comprising 1900 images, with 950 images belonging to the "Fire" and "No-Fire" class, respectively. The dataset is divided into an 80% and 20% for training and testing purposes, respectively. The training set is further divided into 80% for training and 20% for validation. The distribution of images on each set can be seen in Table 1.

2.2. ResNet50V2

In this study, we use a pre-trained ResNet50V2 model as the backbone of our proposed approach, due to its effectiveness in various deep learning tasks [18, 19, 23]. A pre-trained ResNet50V2 model is initialized with pre-trained weights from the ImageNet dataset, which aids in capturing general image features.

2.3. Data Preparation

To prepare the dataset for training, all images were resized to a uniform size of 224 × 224 pixels to leverage the benefits of the pre-trained ResNet50V2 model, which has been pretrained on large-scale datasets using this specific input size. By resizing the images, we ensure compatibility with the pre-trained model, enabling effective transfer learning.

Furthermore, the pixel values of the input images were scaled between -1 and 1. This scaling process was done to normalize the pixel values and bring them into a consistent range. It helps with the training process, making it more efficient and reliable [24].

(a)

(b)

Figure 1. The overview of dataset used in this study; (a) Fire class (b) No-Fire class.

Table 1. Data distribution on each set.

Class	Training Set	Validation Set	Testing Set	Total
Fire	608	152	190	950
No-Fire	608	152	190	950
Total	1216	304	380	1900

2.4. Proposed Approach

Figure 2. shows the proposed TeutongNet model. To prevent the pre-trained layers of ResNet50V2 from being updated during training, they are set to be non-trainable. Additional layers are introduced on top of the ResNet50V2 to further refine the model. These layers are: global average pooling 2D, dense layer, dropout layer, and a sigmoid output layer. These additional layers enable the model to learn more specific and relevant features for the task of forest fire detection, allowing the model to adapt and specialize in accurately detecting forest fires.

A global average pooling 2D layer is added to aggregate spatial information from the output of the ResNet50V2 model. This pooling operation reduces the spatial dimensions while preserving the essential features [25].

A dense layer with rectified linear activation is incorporated to capture higher-level features and enhance the model's representation capabilities. This layer consists of 256 units, which can be adjusted based on the specific requirements of the forest fire detection task. To avoid overfitting, a dropout layer is included after the Dense layer. This layer randomly drops out a fraction of the input units during training. By randomly dropping out a fraction of input units, the dropout layer ensures that no individual unit can rely too heavily on specific features or correlations present in the training data. This forces the network to learn more robust and generalized representations of the data, as it cannot rely on the presence of specific units during training [26].

Finally, the final predictions are produced by adding a dense layer with 1 unit and sigmoid activation. This layer represents the probability, with values greater than 0.5 indicating “No-Fire” class and values less than or equal to 0.5 indicating “Fire” class.

Table 2. shows the parameter that we used to train TeutongNet model. We trained the model for 25 epochs and the batch size was 32, allowing the model to iteratively learn from the training set and improve its performance over time. TeutongNet also optimized using the Adam optimizer with a learning rate of 0.001. The choice of Adam optimizer and learning rate was based on their effectiveness in deep learning tasks. Binary cross entropy was used as the loss function, which is suitable for binary classification problem.

2.5. Model Evaluation

In this study, we employed several evaluation metrics to assess the performance of the model. These metrics included accuracy, precision, recall, and F1-score. The equation for accuracy, precision, recall, and F1-score can be seen in equations 1, 2, 3, and 4, respectively [27].

$$Accuracy = \frac{TP + FN}{FP + FN + TP + TN} \tag{1}$$

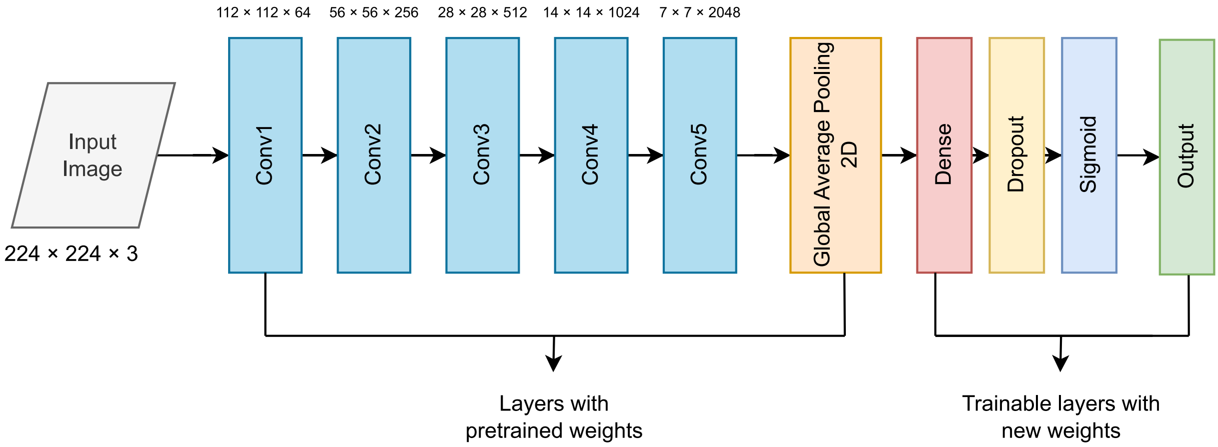


Figure 2. The proposed TeutongNet model. Modified from [28].

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

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

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

where TP stands for the number of correctly identified positive cases, FN represents the number of cases mistakenly classified as negative, FP indicates the number of cases mistakenly classified as positive, and TN represents the number of correctly identified negative cases.

Additionally, we plotted an ROC (Receiver Operating Characteristic) curve to visualize the model's performance in terms of its true positive rate (TPR) against the false positive rate (FPR) at various classification thresholds. The area under the ROC curve (AUC) was also calculated as a measure of the model's discriminatory power.

3. Results and Discussions

In this study, TeutongNet model was trained for the detection of forest fires. The objective was to achieve an improvement in accuracy compared to the existing models, in order to enable early detection and intervention, thereby minimizing the devastating impact of forest fires.

The training and validation accuracy as well as the training and validation loss during the training process of TeutongNet model can be seen in Figure 3. It demonstrates that the model effectively learns from the training data, as evidenced by the increasing training accuracy and decreasing training loss. Moreover, the similar performance on the validation data, as shown by the convergence of validation accuracy and validation loss, indicates that the model generalizes well and is capable of making accurate predictions on new, unseen examples.

Table 2. Parameter used to train TeutongNet.

Parameter	Value
Batch Size	32
Optimizer	Adam
Learning Rate	0.001
Loss function	Binary cross entropy
Epoch	25

Table 3 presents the performance metrics of the trained TeutongNet model for detecting forest fires on the test set. The model achieved an accuracy of 98.68%, indicating its ability to correctly classify “Fire” and “No-Fire” instances. The precision score of 99.47% signifies a low false positive rate. The recall score of 97.93% indicates the capability of the model to capture a high proportion of actual fire instances. The F1-score of 98.68% combines precision and recall, providing an overall measure of the model's performance. In this table, we also compared the performance of our proposed TeutongNet with a pre-trained ResNet50V2 without modification. The results demonstrate that the modifications made in TeutongNet, including the introduction of additional layers, have significantly improved the model's performance for forest fire detection. The introduction of a global average pooling 2D layer helps capture important features and reduce input dimensionality. A dense layer follows, enabling the model to learn complex relationships between extracted features. This layer enhances the model's ability to identify high-level representations relevant to forest fire detection. Moreover, a dropout layer prevents overfitting by randomly deactivating

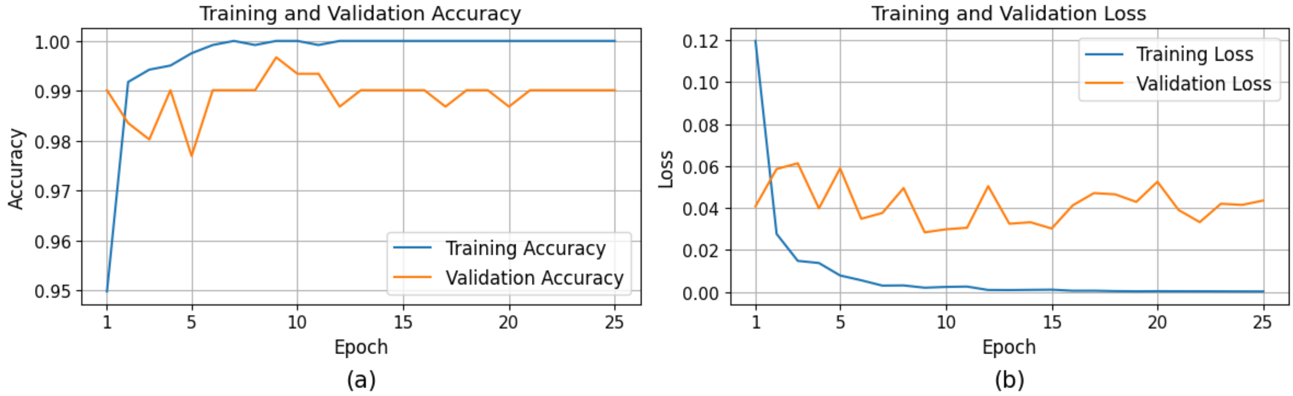


Figure 3. Training and validation result (a) accuracy and (b) loss.

Table 3. Performance of TeutongNet and ResNet50V2.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Proposed TeutongNet	98.68	99.47	97.93	98.68
Pre-trained ResNet50V2	94.74	98.30	91.05	94.73

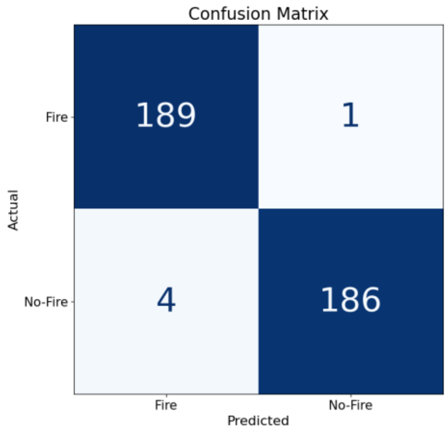


Figure 4. Confusion matrix on testing set.

neurons during training, encouraging better generalization and reducing reliance on specific training data features.

To gain a more detailed understanding of the model's predictions, the confusion matrix in Figure 4 provides a breakdown of its classifications. It provides a more detailed breakdown of the model's predictions. In this case, the model correctly classified 189 images as "Fire" and 186 instances as "Fire." However, it made 1 false positive prediction, incorrectly classifying a “Fire” image as "No-Fire," and 4 false negative predictions, incorrectly classifying “No-Fire” images as "Fire."

The false positive and false negative predictions with its confidence score can be seen in Figure 5. It can be seen that the false negative predictions occur on images with small fires in size and areas where the surrounding forest or vegetation is not visibly burned or significantly affected. In such cases, the fire might be difficult to detect, especially if it is not accompanied by large-scale smoke or visible flames. In case of false negatives, the predictions could be attributed to the visual characteristics of the images that resemble fire, such as the presence of smoke or an orange tint. These visual cues might lead the model to mistakenly classify these images as containing a fire. Smoke and the orange color associated with fire are common indicators that humans often associate with fire occurrences.

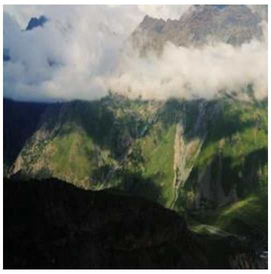
Figure 6 displays the ROC curve for the TeutongNet model. It shows the model's excellent performance, with an AUC score of 0.998. The AUC score indicates the overall effectiveness of the model in accurately classifying instances, with a score close to 1.00, the model demonstrates a high degree of accuracy and reliability in distinguishing between “Fire” and “No-Fire” images.

The performance of our proposed TeutongNet was compared to other works, as shown in Table 4. TeutongNet achieved higher accuracy compared to other works, indicating that our model performed better for forest fire detection. While S. Khan et al [11] achieved higher recall, our proposed TeutongNet achieved higher precision. This indicates that when our model predicts a fire, it is highly likely to be an actual fire event. The emphasis on precision is crucial in forest fire detection scenarios, as accurate and reliable predictions are vital for timely and effective response measures.

Overall, our proposed TeutongNet achieved high performance in forest fire detection. By introducing additional layers on top of ResNet50V2, TeutongNet further refines the feature extraction process. These layers enhance the model's ability to capture and understand complex patterns and relationships specific to forest fire detection, leading to improved performance.


Predicted = No-Fire
(Confidence Score = 99.32%)

(a)


Predicted = Fire
(Confidence Score = 99.66%)


Predicted = Fire
(Confidence Score = 99.96%)


Predicted = Fire
(Confidence Score = 62.38%)


Predicted = Fire
(Confidence Score = 99.99%)

(b)

Figure 5. (a) False negative prediction and (b) false positive prediction.

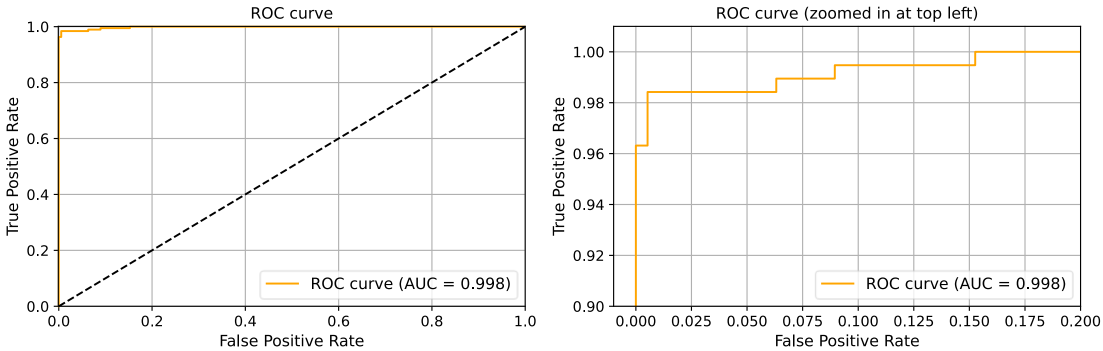


Figure 6. (a) ROC curve and (b) zoomed ROC curve.

Table 4. Comparison of propose approach with previous works.

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Proposed TeutongNet	98.68	99.47	97.93	98.68
S. Khan et al [12]	98.42	97.42	99.47	94.96
A. Khan et al [22]	95.00	95.70	94.20	94.96
Sun et al [13]	94.10	-	-	-
Sousa et al [29]	93.60	94.1	93.1	-
Tang et al [30]	92.00	-	-	-
Govil et al [14]	91.00	-	-	89.00

4. Conclusions

This study addressed the need for accurate and timely detection of forest fires by proposing TeutongNet, a modified ResNet50V2 model. By leveraging transfer learning and incorporating additional layers, TeutongNet achieved remarkable performance in forest fire detection. The model's accuracy, precision, recall, and F1-score demonstrate its ability to correctly classify fire and non-fire images. The ROC curve analysis further confirms the model's strong discriminatory power. The findings highlight the potential of deep learning models for early detection and response to forest fires. Implementing such models can significantly contribute to mitigating the devastating impact of forest fires and protecting valuable ecosystems. Future research can focus on scaling up the model and integrating it into real-time fire monitoring systems for effective fire management.

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