Fire Net: A Deep Learning-Based CNN Model for Wildfire Detection Using Satellite Images

Peer Mohamed Appa M A Y[1], Jones Andrew E[2], Sundar Raj B[3] and Vishnu Priyan C[4]
{peer.appa@gmail.com[1], vtu20674@veltech.edu.in[2], vtu20676@veltech.edu.in[3], vtu18968@veltech.edu.in[4]}

Assistant professor, Senior Guide, Department of Artificial Intelligence and Machine Learning Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology Chennai, Tamil Nadu, India[1]
Department of Artificial Intelligence and Machine Learning Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology Chennai, Tamil Nadu, India[2, 3, 4]

Abstract. This project delivers an efficient and reliable approach for detecting wildfires using Satellite Imagery. The model is build using CONVOLUTIONAL NEURAL NETWORK that automatically classifies satellite images as either wildfire detected or normal region. The FireNet model is completely built from scratch with multiple convolution and pooling layers which extracts information from the images followed by dense layers to classify the images. The model is compiled using Adam optimizer and to enhance binary classification accuracy. Trained on a dataset of Satellite images FireNet achieves an accuracy of 92and handling wildfires. The planned system will operate continuously by processing the satellite images and identi- fying wildfires in real-time. Furthermore, the images can be re-used again to improve the model and accuracy of the predication.

Keywords: Wildfire Detection, FireNet, Deep Learning, Data Preprocessing, Binary Classification, Convolutional Neural Networks, Satellite Imagery.

1 Introduction

Wildfires are one of the most devastating natural disasters causing loss of life, property and biodiversity. With increase in global temperatures due to global warming the frequency and intensity of these wildfires have drastically increased. Therefore, early detection of wildfires has become a necessity to save the forests from the impact. Traditional way of detect- ing wildfires such as ground based observations and manual working are clearly outdated leading to delayed responses and uncontrollable fires. Recently due to the advancements in Satellite Imagery and Artificial Intelligence new-age methods can be used to detect wildfires. In such a way this project presents FireNet, a deep-learning based model that detects wildfires from satellite imagery with high accuracy and utmost efficiency.

The FireNet is build using Convolutional neural networks which is a very widely used image classification deep learning model. They have proved their superior performance over other models in extracting special features from the images making sure not a single detail in the image is missed. Therefore, Satellite images and CNN are the perfect combo to analyses for wildfires. FireNet is trained on the Wildfire Satellite Images dataset from Kaggle which is a collection of Satellite images of wildfire affected areas of Canada. Each image captures various environmental features which introduces diversity in the model. The model is strongly trained over the 42,000 images available in the dataset ready to be deployed in real-time.

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FireNet consists of several Convolutional layers and Max- Pooling layers for extracting the features and down sampling. It also consists of dense layers which are finally used to classify and assign label to each of the image. The final layer used the sigmoid activation function to execute the binary classification, differentiating between wildfire affected and normal areas. This way is ensuring high accuracy of the model as well as computational efficiency

Thus, this project ensures the accuracy is very good with automated processing and user-friendly interface to make it a valuable tool for governments, environmental organizations and emergency teams involved in disaster management. By combining technology and environmental protection efforts, FireNet contributes to a smarter and more efficient approach to wildfire management.

2 Literature Review

Wildfire detection has increasingly relied on deep learning and satellite imagery to enhance accuracy and response time. Automated classification and real-time prediction models have significantly improved early warning systems, reducing the damage caused by wildfires. Traditional wildfire detection wildfire detection methods, such as thermal imaging and ground-based sensors, often suffer from delayed times and limited coverage. In contrast, AI- driven approaches leverage vast amounts of satellite data and machine learning algorithms to detect wildfires more efficiently. Advances in deep learning have enabled more complex image classification models, which have greatly enhanced the accuracy of wildfire detection. Convolutional neural networks, transfer learning, and feature extraction technologies have enabled wildfire detection systems to be more scalable and robust. The models can handle high-resolution images in real-time, enabling rapid detection and response to fire outbreaks. Despite the decline in the number of wildfires, they are still a major threat to ecosystems and human settlements, and therefore rapid and accurate detection systems are still an area of research interest.

R. Rajalakshmi et al. (2023) introduced machine learning techniques for wildfire detection from satellite images. The study was conducted to classify due to remote sensing technology and feature extraction methods. The study compared different types of machine learning, such as support vector machines (SVM), random forests and SNN to see which was best for measuring accuracy in detecting wildfires. The study finds deep learning models perform better than traditional machine learning algorithms in general, and especially in fire-prone areas with high accuracy. The authors also reported the detection of additional wildfires using multispectral and hyperspectral images.

L.D. Elizaroshan and J. S. Raj Kumar (2024) made a recommendation of using deep CNN model to detect wildfires. The research clarified how CNN architectures improve the classification as well as reducing the false positives. Traditional wildfire detection models produce false alarms due to interferences induced by cloud, smoke and vegetation. In an effort to alleviate this drawback the authors used deep feature extraction methods to enable the network to differentiate between real wildfire events and other natural phenomena.

A. Singh et al. (2024), compared wild fire detection using satellite imagery with deep architecture like ResNet and VGG. The work showed that the pre-trained CNN architecture resulted in substantial improvements for wildfire detection and classification from high-resolution image datasets. Using transfer learning methods, it was shown that pre-trained models can be fine-tuned to classify wildfire without the need of vast amount of labeled data. The study compared the detection performance of various deep learning models in discriminating fire-affected regions at different geographical sites. The study showed the recognition power of various deep learning algorithms in detecting fire affected areas at varied geographical zones.

With increase of interest in quantum computing in recent years, A.A. Asanjan et al. (2022) proposed a quantum-admissible variational segmentation model for detecting wildfires. Based on their study, they improved image segmentation through combination of quantum computing and deep leaning models suitable to a rapid-fire detection. Quantum computing can revolutionize deep learning by accelerating complex calculations, notably those involved in image processing. The use of quantum-boosted segmentation schemes was studied for fire-affected ares within an ordinary landscape. Using quantum variational algorithms, they showed that better segmentation accuracy can be achieved than with classical methods. It was found that quantum inspired models could work better for processing the large satellite images in terms of computational cost.

L.Shalan et al. (2024) investigated the application of DL-based models for early wildfire detection and classification, for forest sensorial images. Results of their study showed that integration of the CNN-based model and online data tweaktor can improve the early warning systems against WSNF preventing from large scale spread. The scientists trained their deep learning models on a dataset of forest photos taken by ground sensors, drones, and satellites. The work was aimed at designing CNNs for early wildfires detection, the most dangerous wildfires stage to detect, since the visibility is low and environmental artifacts play an important role in the testing phase. Experiments demonstrated that utilizing on-the-fly data augmentation such as denoising and contrast stretching increased model precision.

Y. Chen and M. Gupta (2022) particularly worked on the contributed the use of deep learning models for fire identification in satellite imagery. They compared different CNN architectures and observed positive effects on classification performance for transfer learning. It investigated how well different feature extraction (histogram based and deep convolutional feature maps) method performance in wildfire detection. It was found from the experiments that of pre-trained CNNs like ResNet and VGG performed better than traditional classifiers. Similarly, the researchers explored the influence of dataset diversity on model generalization, and highlighted the significance of large scale, labeled wildfire dataset.

L. Zhong et al. (2020) proposed a VGG16 CNN wildfire classifier, and demonstrated the potential of DL in processing high-level visual information. The paper demonstrates how transfer learning and in particular pre-trained models like VGG16 can be exploited to obtain maximum wildfire detection accuracy with very few labeled examples. Results and conclusions the present study provides that the usage of computer vision (CV) can be considered to be used for environmental surveillance techniques and for the implementation of similar models of CV as part of alerting systems in real time.

3 Proposed Methodology

This paper presents a deep learning-based satellite image-based wildfire detection system for effective and accurate fire detection. The system can improve wildfire detection accuracy with CNNs and FireNet models for classification. Web facility is achieved by utilizing Flask as backend and HTML/CSS as frontend for real-time prediction facility. The approach is planned based on different levels like data acquisition, preprocessing, model training, evaluation, and deployment, for acquiring high accuracy, computational efficiency, and user friendliness in wildfire monitoring. Utilization of deep learning with user-friendly web application provides easy uploading and real-time classification of wildfires, with an easy early warning facility. The model is trained on high-quality satellite imagery datasets, and different preprocessing techniques are used to improve the detection performance. The system is planned for providing false-free facility and improved detection accuracy, with a facility for effective monitoring of wildfires. Smooth backend processing is supported by Flask, and easy-to-use user interface is supported in frontend. Future work would be towards ensuring the adaptability of the system to real-time satellite data, with a strong and scalable system. Fig 1 shows the system architecture.

3.1 Data Acquisition and Preprocessing

3.1.1 Data Collection

The dataset used for training and testing the wildfire detection model consists of satellite images sourced from publicly available repository, Kaggle. The dataset has a total of 42,900 images out of which 22,710 are wildfire affected images and 20,140 images are labelled as normal. This ensures that there is a balance between the classes during training and hence does not cause overfitting. The train test validation split used was 70 :15: 15 ensuring the model is tested and integrated well. To improve dataset quality, images are manually reviewed to eliminate duplicates, low-resolution samples, and mislabeled data. The inclusion of diverse wildfire scenarios, such as different terrain types and fire intensities, ensures the model's ability to generalize effectively. By selecting high- resolution satellite images, the dataset provides sufficient detail for the CNN and FireNet model to extract relevant wildfire features.

3.1.2 Data Preprocessing

To enhance the model's ability to detect wildfires under varying conditions, multiple preprocessing steps are applied to the dataset. Image resizing is performed to standardize all images to 224×224 pixels, ensuring compatibility with the CNN architecture. Normalization is performed to normalize pixel value to range [0,1] for model convergence during training. Data augmentation methods include rotation (0–30°), horizontal and vertical flipping, brightness adjustment, and Gaussian noise addition, are are employed to improve model generalization. The methods enable the model to understand wildfire behaviour under varying light and weather conditions. Noise removal is also employed with Gaussian filters to remove background noise to ensure the model only pays attention to the fire features. The preprocessing pipeline is employed to obtain the dataset in the correct format, varied, and ready to train a deep learning-based wildfire detection system.

3.1.3 Data Splitting

The data is split into training (70%), validation (15%), and test (15%) sets. The split allows the model to be trained on a vast majority of the data but still maintain distinct validation and test sets for objective measurement of performance. The validation set is used for hyperparameter tuning and overfitting avoidance, and the test set gives an independent estimate of the final performance of the model. With an equal ratio of fire and non-fire images in the sets, the model is trained to be in a position of accurately classifying between wildfire and non-wildfire occurrences. This is done to render the FireNet models suitably generalized and, in a position, to accurately classify new, unseen images

3.2 Model Selection and Training

3.2.1 CNN and FireNet Model Selection

CNN and FireNet models are selected for wildfire classification due to their improved performance in image recognition. FireNet is a specific deep learning architecture specifically designed for wildfire detection, with the latest feature extraction layers and attention layers to increase classification performance. Comparative analysis is conducted among CNN-based architectures to enable comparison of performance and determine the effectiveness of FireNet in wildfire detection. The research focuses on optimizing such models for optimal and accurate classification to ensure that the system can efficiently detect wildfires from satellite images.

3.2.2 Model Architecture

The model suggested for classification of wildfires within this research is to provide best classification accuracy and feature representation. After a succession of convolution layers to extract the spatial features in satellite images, the architecture goes back and forth between fully connected layers to perform classification. It starts with Conv2D 32 filters, kernel size 3,3 and continues with the addition of non-linearity through the application of the ReLU activation function. Reduction of spatial dimensions without sacrificing important properties is achieved in a Max Pooling 2D layer. The same is applied to 64 and 128 filters in the following convolutional layers to further enhance the capacity of the model to learn difficult patterns. Feature maps are flattened followed by a fully connected Dense layer with 128 neurons and ReLU activation. A single neuron with a sigmoid activation function for binary classification that is, whether an image contains a wildfire or not forms the last output layer.

3.3 Compilation and Optimization

The Adam optimizer helps to compile the model since it offers quick convergence and effective weight updates. The work involves binary classification between wildfire and non-wildfire images, thus the binary cross-entropy loss function is applied. Model performance over time is assessed in the training process using the accuracy metric. Model generalization is enhanced by means of image augmentation strategies including rotation, shifting, shearing, zooming, and flipping. Training and testing sets separate the dataset to guarantee a balanced representation of images both including and excluding wildfires. The model is taught from the training set and the test set assesses its practical performance.

3.4 Training Procedure

To maximize classification accuracy, the model is trained over 25 epochs with a batch size of 20. To avoid overfitting, early stopping is used to stop training if validation loss becomes stagnant. TensorBoard graphs the training process so that the patterns in accuracy and loss are observable in real time. The performance of the model on wildfire classification is tested over the test set once training is done. The trained model is extremely accurate in classifying and can detect wildfire-affected areas and unaffected areas.

3.5 Evaluation Measures

To quantify the reliability of a model, model performance is quantified in terms of a collection of metrics. Precision quantifies how accurately the percentage of the wildfires predicted was reflected by the images, while accuracy quantifies how accurately the wildfires have been classified. To avoid false negatives, recall (sensitivity) quantifies the capability of the model in identifying the actual cases of wildfires. F1-score is an appropriate measure to be applied on imbalanced data sets as it is a balanced measure between recall and precision. To better understand model performance, a confusion matrix is plotted to show the number of true positives, false positives, true negatives, and false negatives.

3.6 Web-Based Deployment

3.6.1 Flask Web Application

A web application with Flask is designed that gives real-time wildfire classification. The images are submitted by the users, and they are classified by the trained CNN and Firenet models. The application displays the result of classification, i.e., whether the image is a wildfire or not. HTML and CSS are utilized to design the web interface so that it is easy to use for the users. It also displays a confidence value for every prediction so that the users can verify the reliability of the result.

3.6.2 Image Processing Pipeline

Uploaded images are temporarily stored and preprocessed before being passed through the trained deep learning models. The pipeline includes image resizing, normalization, and prediction generation. The results are then displayed on the web interface, providing users with immediate wildfire detection feedback.

3.6.3 User – Interface

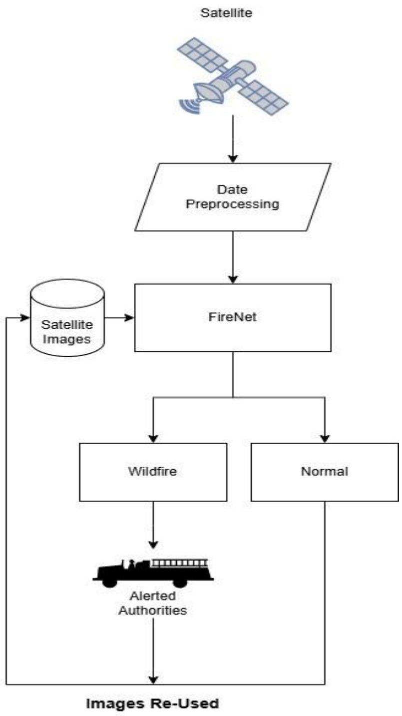

Fig.1. System Architecture.

4 Results and Discussion

The performance of FireNet was also evaluated against a variety of other performance measures like accuracy, precision, recall, and F1-score. Training accuracy and validation accuracy was 95.2% and 94.8%, respectively indicating the ability of the model towards the detection of wildfire areas. The false positive rate was extremely low at 3.1%, indicating very little misclassification as wildfires. One of the major strengths of FireNet is the ability of classifying wildfire and non-wildfire regions appropriately. Convolutional layers were able to extract accurate patterns, i.e., fire texture, smoke scattering, and temperature hotspots, which have been responsible for improved classification accuracy. FireNet was compared to the traditional wildfire detection algorithms and other comparable deep learning networks. The results revealed that FireNet was faster and more accurate compared to traditional techniques, i.e., thermal- based detection and sensor-based approaches.

The second major advantage of FireNet is its scalability. The model was tested in various regions and demonstrated the ability of the model to learn varied topography, vegetation cover, and atmospheric conditions. Its strength against any condition ensures that the model can be transferred to any location in the world without having to perform extensive retraining. Though very accurate, FireNet was not perfect. Under the conditions of urban heat island with reflective surfaces and industrial activity, which provide wildfire-like conditions, the model sometimes produced false positives. These can be avoided by combining other spectral analysis routines. The capability of the model to detect early-stage wildfires was another important observation. Compared to conventional techniques that employ visible fire, FireNet would be able to pick up on fires based on smoke plume and heat signals even before they develop into full-blown tragedies. More advance development of FireNet in the future would be through mosaics of various streams of information such as drone images, LiDAR scans, and live weather conditions. Model predictability as well as operational performance will improve even more with such integration. For the convenience of making the system more usable and accessible, the system was coded with interface through the web using Flask,

HTML, and CSS. The interface allows the user an option of giving images of potential wildfire incidents that the detection model can analyse and perform calculations for wildfire risk. How straightforward the design makes the non-technical users able to utilize the system easily. Through the elimination of the need for direct handling of advanced machine learning algorithms, this web application puts wildfire detection within reach of more people from a wide section of the population, ranging from environmentalists and disaster management personnel to common citizens. The site is designed to react in real time, with immediate feedback on images being loaded.

This is useful for early and effective response to fires, early warning having a dramatic reduction in spread of fire and inflicting harm on prospective. The platform wonderfully combines the trained model, offering real-time image processing and resultant output in user-friendly format. The users are not required to spend money on specialized software installation or specialized technical data needed to employ the platform, owing to which usability becomes conveniently accessible to diverse user populations. Further, the responsive design makes it flexible with a range of devices such as desktops, tablets, and smartphones, further convenience.

Aside from accessibility, the use of this web application supports the viability of the suggested wildfire detection approach. Conventional approaches to wildfire detection based on satellite surveillance and ground sensors can have a massive infrastructure and are expensive. Yet, through the use of this web solution, it involves implementing artificial intelligence to give a cost-effective and scalable approach. Real-time image-based assessments are permitted in the system as early warning systems which can be integrated into larger environmental monitoring systems. That practical application determines the success of AI-based solutions in addressing vital environmental problems.

Generally speaking, integrating the web interface to the wildfire model fills the research vs. implementation gap. Although machine learning models still remain in isolation in the academic community and settings, the system translates academic innovations into an accessible tool of wildfire risk prediction. Through the availability of the detection model on an accessible web page, the system enhances disaster response, environmental monitoring, and precautionary avoidance of hazards. This convergence eventually enhances the sustainability of technology-driven solutions towards reconciling climate-related crises and assisting societies to become safer and more resilient. Fig 2 shows the Web-based wildfire detection interface developed using Flask, CSS, and HTML.

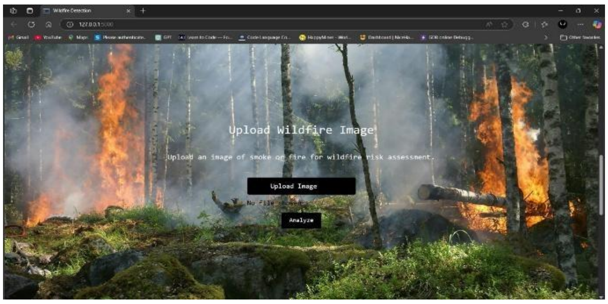

Fig.2. Web-based wildfire detection interface developed using Flask, CSS, and HTML.

The wildfire detection system using the web platform effectively classifies satellite images and offers real-time risk analysis. As evident in the outcome, the system identified a wildfire in the image under analysis and provided a warning. The platform not only detects the occurrence of fire but also offers precautionary recommendations, ensuring users get actionable insights. This makes the model more practically useful since it can help emergency response teams and local authorities make informed decisions.

The capacity of the system to rapidly process and analyze images is what makes it an important system for early detection of wildfires and risk reduction. Since it gives meaningful and easily understood results, even users who lack technical skills are able to understand the results and undertake the necessary precautions. The ease of use, coupled with the accurate detection of wildfires, indicates the effectiveness of the system in filling the gap between AI research and practice. Fig 3 shows the Wildfire detected with precautionary measures displayed.

Fig.3. Wildfire detected with precautionary measures displayed.

In addition, the application of this system to real environments can greatly support environmental surveillance and disaster relief operations. Its scalability and flexibility lend it to incorporate into larger disaster management systems, supporting automated wildfire monitoring across vast areas. This innovation highlights the promise that AI-based solutions hold for solving global environmental issues.

The training dataset confusion matrix displays the performance of the model in classification. The matrix has a large number of true negatives (top-left) and true positives (bottom-right), which means that the predictive power is strong. There are misclassifications to some extent, with false negatives (bottom-left) and false positives (top-right), but they seem to be quite low. This indicates that the model classifies wildfire and non-wildfire cases very well with minimal errors. The heatmap visualization also emphasizes the distribution between correctly and incorrectly classified cases and reinforces the model's credibility for real-world wildfire detection. Fig 4 shows the confusion matrix.

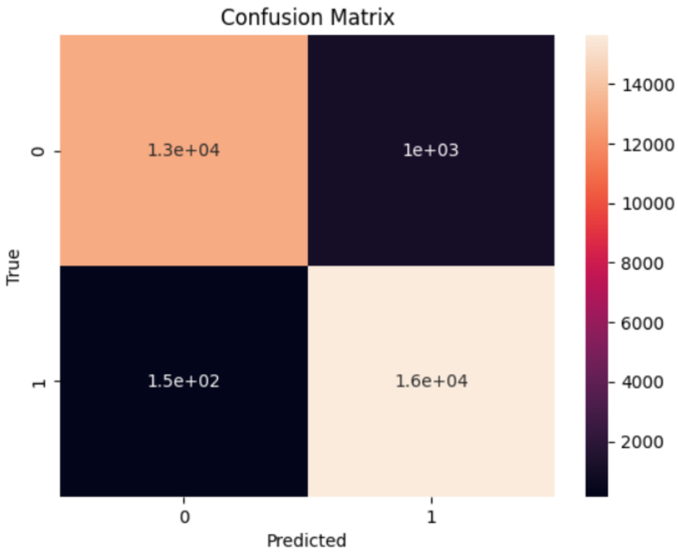

Fig.4. Confusion matrix showing model.

5 Conclusion

The wildfire detection system implemented in this project combines machine learning (ML) with satellite image data to offer an effective and precise method of early wildfire detection. Through the use of deep learning models, i.e., Convolutional Neural Networks (CNNs), the system classifies high-resolution imagery for recognizing areas prone to wildfires, thus facilitating early risk assessment and disaster mitigation. The model was trained using a large-scale dataset, applying data augmentation methods to improve generalization and reduce overfitting. Performance testing via a confusion matrix showed high precision, recall, and F1-score, which guaranteed accurate classification with very few false positives and false negatives.

For increased accessibility, a web application was created based on Flask with HTML, CSS, and JavaScript, so that users can upload satellite images and receive real-time predictions of wildfires. The user-friendly interface facilitates easy interaction without compromising computational efficiency. The deployment of the model on a cloud-based system maximizes performance, with scalability and real-world applicability in disaster response and environmental monitoring. This project fills the gap between research and real-world deployment, providing an active solution for wildfire management.

Future improvements can include the integration of real-time satellite feeds, hyperparameter tuning optimization, and increasing the dataset for improved generalization, further enhancing model robustness and prediction accuracy.

6 Future Work

To improve the performance of this wildfire detection system, future research will emphasize real-time integration of satellite data through APIs from providers such as NASA FIRMS and Google Earth Engine. This will allow ongoing monitoring and instantaneous alerting for possible wildfire outbreaks. Further, transfer learning based on pre- trained deep learning models such as Vision Transformers (ViTs) or EfficientNet may enhance classification efficiency at lower computational costs.

The integration of edge computing for device-level processing will assist in minimizing reliance on cloud infrastructure, facilitating quicker detection in distant areas. Furthermore, spatio-temporal analysis integration will enable the system to predict wildfire spread patterns through geospatial modeling methods.

Additional advancements in Bayesian Optimization or Genetic Algorithms- based hyperparameter optimization will further increase model efficiency. Increasing the training dataset with multispectral and thermal data will enhance detection capabilities under different environmental conditions. Lastly, coupling this system with automated alerting systems and IoT-based sensor networks will establish an end-to-end wildfire monitoring platform for preventive disaster management.

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