Wildfire image prediction using CNN and ResNet50 model

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***Abstract*—Forest fires represent a significant global challenge due to their devastating impact on ecosystems, human lives, and economies. These fire incidents have a lot of ecological and environmental effects, such as habitat loss, higher carbon emissions, and the possible loss of species. The increasing frequency and intensity of forest fires, driven by factors such as climate change and human actions, emphasizes the need for efficient early detection and containment strategies. We study Quebec region of Canada using MODIS fire data and QGIS for better analysis. Our study leverages remote sensing technologies along with deep learning (DL) methodologies, focusing on Convolutional Neural Networks (CNNs) and ResNet50, which are used for automatic feature extraction and classification capabilities. Our research aims to significantly enhance the effectiveness and accuracy of forest fire and smoke detection by leveraging these advanced methods.The results of our study demonstrate the exceptional performance of the CNN model, with an impressive classification accuracy of 96.37 percent. We do comparative analysis of CNN and ResNet50 model using different metrics. This research contributes to the advancement of early forest fire detection, with the potential to mitigate the extensive ecological, economic, and societal impacts of forest fires.**

***Index Terms*—Forest fire, Remote Sensing, Deep Learning, CNN, ResNet50, QGIS**

I. Introduction

Forest fires are a serious problem because they destroy ecosystems, risk human life, and cause huge financial losses. These catastrophes have significant ecological and environmental ramifications, including habitat destruction, elevated carbon emissions, and the possibility of biodiversity loss, regardless of whether they are caused by human activity or natural causes [1]. Because wildfires are hard to reach and there are a lot of things that can catch fire in wooded areas, it can be hard to put them out quickly and effectively. In addition, effective early discovery and containment methods are needed because they are happening more often and with more force because of climate change and human activities [2]. The effects of forest fires on our environment, economy, and society are extensive and severe. They put people's lives in danger in the impacted areas and cause huge losses in terms of the economy and environment.

Millions of hectares of forests are destroyed by these fires every year, which increases carbon dioxide levels and oxygen loss, both of which can worsen climate change [3]. Furthermore, forest fires severely harm wildlife by destroying their habitats and reducing biodiversity. Forest fires degrade the air quality, causing respiratory disorders and other health problems in both people and animals. These emissions also include smoke and other pollutants. Additionally, they degrade land and cause erosion over time due to their long-term effects on soil quality. In addition to causing significant emissions of carbon dioxide into the atmosphere, these fires exacerbate climate change [4]. Their effects go beyond financial losses to include devastation of infrastructure and timber resources [5].

Given that forest fires have the potential to cause high damage to large area of land and result in fatalities, it is necessary that they are detected promptly in order to minimise the consequences. A number of factors, including prolonged droughts, high temperatures, and human negligence, are linked to the rise in forest fires [6]. Forest fires on a large scale can do a lot of damage, which shows how important it is to plan and handle them well to avoid disaster. The adoption of DL and traditional machine learning techniques has been prompted by the shortcomings of traditional forest fire detection systems, which are frequently insufficient in wide-open outdoor environments [7].

CNN is a potent model for automatically extracting features and classifying them. It has also done better than traditional machine learning methods at finding trends and outliers. Finding forest fires and smoke in new ways is the focus of this study, which stresses accuracy and early warning systems. Deep learning, hybrid techniques, and advanced object recognition are all combined in the suggested model. It uses the power of the ResNet50 and CNN models to rate the performance of the system. CNN achieves an impressive 96.32 percent accuracy rate in classification jobs. The system is great at more than just classifying; it's also great at analyzing trends and finding outliers, which makes it much more accurate at finding forest fires. This study is a big step toward making fire warning systems that are more accurate, timely, and effective. This could have effects on protecting the environment and keeping people safe. [8] [9].

We investigate a hybrid system that blends deep learning and remote sensing technology in order to accomplish these objectives [10]. In addition, we present a collaborative region detection and grading framework that makes use of a lightweight

CNN and weakly supervised fine segmentation to tackle the problem of forest fire detection and grading. Our goal is to increase the accuracy and effectiveness of the crucial job of detecting forest fires and smoke by utilising these methods.

II. Related Works

The study in [11] looks into how forest fires in India affect the production of ecosystems and terrestrial carbon emissions from 2003 to 2017. The productivity and biodiversity loss in terrestrial ecosystems was quantified by making use of existing remote sensing techniques. In order to understand the relationship between forest fires and ecosystem productivity, the study used burn indices derived from satellite remote sensing. Two light use Efficiency (LUE) models were applied to measure ecosystem production and carbon emissions. To evaluate the effect of forest fires on the output of natural ecosystems and terrestrial carbon emissions, Net primary productivity (NPP) was employed as a stand-in.

In [12],digital classification techniques and satellite images were used to assess the burnt area caused by forest fires in Uttarakhand. The burned area was estimated to be 3774.14 km2, or 15.28 percent, of the state's total forest area. Three different dates' worth of satellite images were used to analyse the cumulative progression of forest fires. Overlay analysis was used to analyse the results at the district, administrative, and forest division levels. The results can be applied to plan mitigation strategies to reduce the impact of wildfires on the environment.

[13] studies about decrement of forest cover on Earth as a result of urbanisation, land use changes, and extreme weather. An important factor for this loss is forest fire, which burns millions of hectares of land every year. In addition to having an effect on the environment, these fires raise carbon emissions worldwide. The Western Ghats of India, a region renowned for its biodiversity and high population density, have seen a rise in the frequency of forest fires, which has severely harmed property, human life, and ecosystem services. Sustainable forest management depends on effective management of forest fires, and cutting-edge environmental monitoring technologies like machine learning and remote sensing which can help predict fire susceptibility in the mosaic of southern India's forests and farms.

In [14], author focuses on the absence of research investigating the correlation between forest fires and climate in Uttarakhand. It highlights how the intensity and spread of wildfires are impacted by climate change on a global scale. The Fuel Moisture Index and Angstrom Index are used in the study to evaluate the forest fires. A negative relationship between relative humidity and forest fires has been observed in earlier studies, suggesting that low atmospheric relative humidity affects fuel moisture. The study also discusses how forest fires cause a loss of carbon stored in the biomass carbon stock of forests.

In [15], A dynamic model was created to help authorities identify the best ways to put out forest fires by simulating their spread. To determine the fire's origin and predict flame temperature, the model makes use of a fire simulation model based on the Kalman Filter. Nevertheless, this method cannot support anticipated fire corrections and has lengthy computation times. West California valley forest fire of 2018 and the Amazon Wildfire in 2019 are two recent outbreaks that the authors cite as evidence of the incapacity to prevent and predict forest fires. Markov reinforcement learning model receives input from the model, which creates a generative model using Long-Term recurrent convolutional neural networks (LRCN). Every image was resized to 1700 x 1700 pixels in order to simulate the Markov Decision process during the experiments, which were conducted on an Intel I7-7820X.

[16] studies in detail about forest fire in Central India and its impact on biodiversity. Forest fires are becoming an increasingly significant hazard to biodiversity as a result of human activities and the effects of climate change. They can damage trees, prevent them from growing again, and endanger populations of wildlife and people.. These fires are mostly caused by human activity, but they also have beneficial ecological effects, like encouraging flowering and seed production. The most fire-prone type of vegetation, according to this study (deciduous broadleaf forests), which examines the frequency of forest fires in Madhya Pradesh, over a 20-year period. The spatial analysis identifies high-incidence areas in the southern Vindhyan and Satpura mountain ranges, highlighting the necessity of fire management strategies that are effective in preserving biodiversity and guaranteeing sustainable forest ecosystems in Madhya Pradesh.

The study conducted in [17] utilizes Support Vector Machines (SVM) and Artificial Neural Networks (ANN) to measure the level of fire susceptibility in Indian forests. This study is among the first in list to predict wildfire susceptibility in India using an integrated approach, utilising MODIS fire hotspot data from 2001 to 2020. The study determines the best ML techniques for creating a fire prediction model and emphasizes the importance of basic characteristics pertaining to topography, climate, and forests. It also emphasises how intricately forests, climatic, and topographic factors interact to increase the frequency and intensity of fires. The study recommends effectiveness models that assume dynamic relationships between parameters to accurately predict fire susceptibility with accuracy.

[18] concerns the application ofCNN as the basis for in the formulation of fire detection algorithms designed to identify forest fires in satellite imagery. Many classification architectures have been explored, as fully connected and softmax layers, convolution and max pooling layers, and ROI methods. Due to the limitations of traditional fire control systems in monitoring

large areas and open spaces, algorithms such as AdaBoost and Local Binary Pattern are used. While methods like the Restricted Boltzman Machine and Deep Belief Network have been used for simultaneous fire and non-fire region extraction, deep learning architectures like GoogleNet and SqueezeNet have been used for early flame detection. For real-time forest fire detection, faster R-CNN, YOLO, and SSD architectures have been compared.

III. System model and problem formulation

In this section we define our problem statement, formulate it so that a model can be implemented on it to get desired output. In this research project, our main goal is to apply state-of-the-art deep learning techniques to create a reliable and effective system for identifying forest fires in satellite photos. Forest fires are dangerous for human life and property in addition to being bad for the environment. Because it is necessary for efficient reaction and mitigation activities, the importance of prompt detection cannot be emphasized. Creating a system that can automatically detect and map forest fires from satellite data is the main goal of our research in order to provide precise and timely response.

We use a rich and diversified dataset from ”open.canada.ca” to accomplish this challenging task. This dataset mainly focuses on forest fires that happen in southern Quebec from 1976 to 2017, which is located south of the responsible forest territorial line. It contains a plethora of cartographic information that has been gathered from many sources, such as aerial photos, field surveys, satellite images, and historical records. We do a thorough preprocessing phase on this dataset before using it for model training. The satellite photos will improve in quality and utility throughout this stage. Resizing, normalizing, and augmenting images are all examples of preprocessing tasks. These metrics are critical because they help to normalize the input data and make it suitable for the subsequent deep learning models, both of which improve the models' overall performance.

In the context of forest fire identification in satellite imagery, Convolutional Neural Networks (CNNs) are utilized as the primary approach, with a specific focus on the ResNet-50 architecture. Convolutional Neural Networks (CNNs) have received recognition for their remarkable ability to excel in tasks related to picture classification. This success can be linked to their inherent capability to independently acquire hierarchical features from image input. Within the realm of CNN architectures, ResNet-50 emerges as a prominent and well regarded model, renowned for its remarkable depth and the integration of skip connections. The aforementioned characteristics confer upon it the capacity to effectively capture delicate details inside images while simultaneously preserving robust gradient flows during the training procedure. ResNet-50 is a very suitable option for our research context because to its ability to accurately identify minor image characteristics, which is crucial for effective forest fire diagnosis.

Fig. 1: Aerial images of Quebec

The CNN and ResNet based fire detection process can be mathematically represented as:

$$P(FireDetected|I) = f_{CNN}(I) \tag{1}$$

$$P(FireDetected|I) = f_{Resnet}(I) \tag{2}$$

Where P(Fire Detected—I) signifies the probability of detecting a fire in input image I, and f represents the DL based detection function.

Utilizing image analysis methods, our main objective is to build a forest fire early warning system. Equations and functions of mathematics play a critical role in real-time picture data and sensor networks, which this system will leverage. We must create an algorithm that, in a mathematical setting, applies picture categorization using mathematical operations, continuously checks incoming image streams, and raises alarms when necessary.This process can be represented mathematically as follows:

Let S(t) represent an incoming image stream at time t, and A(S(t)) denote the early warning system's alert function:

$$A(S(t)) = \begin{cases} 1 & \text{, if fire or smoke is detected in the stream S(t)} \\ 0 & \text{, otherwise} \end{cases}$$

The objective of this study is to exploit the feature-extraction capabilities of Convolutional Neural Networks (CNNs) in order to identify patterns related to fires, including flames, smoke plumes, and other pertinent indicators that can be observed in satellite data. One crucial aspect of our study involves doing a comparative analysis of traditional Convolutional Neural Network (CNN) models and the ResNet-50 architecture. This comparison investigation will provide vital insights into the performance of both methods in the unique setting of forest fire detection. Our research project will go into the finer points of the model architectures, explain the subtleties of our training techniques, and clarify the evaluation metrics that support our estimation of the models' efficacy in the next parts. In order to evaluate the overall resilience and dependability of our fire detection system, we will also make use of advanced visualizations and perform a thorough analysis of the data. After that, we will have a conversation about the various uses for our system, from timely notifications to rescue and forest service agencies to a larger discussion about how it might help tackle the serious worldwide problem of forest fires. The importance and urgency of this research are highlighted by the socioeconomic and environmental significance of our work.

IV. The Proposed scheme

In this section of paper we describe the technical procedures needed to finish our study. We concentrate on the steps involved in acquiring data and putting the model into practice. Our research includes preprocessing geographical data, picture analysis, region characterization, application of DL techniques CNN and ResNet50. We also discuss about early detection of wildfire and mitigation strategy development.

We begin our investigation by compiling and organizing information about forest fires in Quebec. We accomplish this by using shapefiles in the QGIS program, which facilitates precise location and organization of fire incidents. For this, we have used MODIS C61 fire dataset to get exact locations of fire incidents throughout the time interval. We are able to precisely geotag photos with each shapefile, which represents a fire occurrence. The data preprocessing serves as an essential basis for the analysis that follows. Following the informational tagging of the photos, we carefully examine every one of them. We are able to locate and extract pertinent photos that are associated with particular fire events by using the information from the shapefiles. To increase their quality and relevance, these retrieved photos are processed using a variety of approaches.In order to separate possible fire patterns and fire-affected areas, which are essential for the ensuing modeling stages, we employ sophisticated image segmentation techniques.

As a first step in improving the model's capacity to generalize, the algorithm preprocesses and augments the data. By performing different picture transformations, the ImageDataGenerator is used to enhance the dataset. Rescaling pixel values to a range of 0 to 1 is one of these transformations, along with shifts, shear, zooming, and flipping horizontally and vertically. With the use of data augmentation, training data can become more diverse and the model is more equipped to manage appearance variations in images, including adjustments to lighting, perspective, and orientation. For reliable picture classification, this is a crucial step. Preprocessed picture batches are produced by the train and validation data generators. From the dataset directory, these generators read and prepare the photographs. Images undergo resizing to a common 256 x 256 pixel size and RGB color mode conversion throughout this process. When training and validating the model, the consistent format of the input data guarantees that the model receives photos of the same size.

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 254, 254, 32)	896
max_pooling2d_3 (MaxPooling2D)	(None, 127, 127, 32)	0
conv2d_4 (Conv2D)	(None, 125, 125, 64)	18496
max_pooling2d_4 (MaxPooling2D)	(None, 62, 62, 64)	0
conv2d_5 (Conv2D)	(None, 60, 60, 128)	73856
max_pooling2d_5 (MaxPooling2D)	(None, 30, 30, 128)	0
flatten_1 (Flatten)	(None, 115200)	0
dense_2 (Dense)	(None, 128)	14745728
dense_3 (Dense)	(None, 1)	129

Fig. 2: CNN Layers added to the model

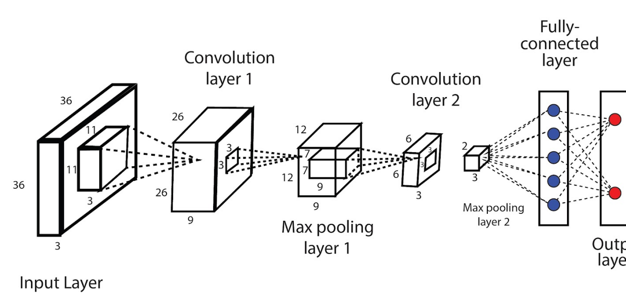


Fig. 3: Working of CNN model

Fig. 3 shows working principle of CNN model on an image dataset. Tensorflow's Keras is used to organize the CNN model into a sequential model. Layers can be added consecutively using the sequential paradigm, beginning with the input and ending with the output. A convolutional layer with 32 filters makes up the first layer. Each of these 3x3 filters is applied to the input image in order to identify features and patterns. The non-linearity is introduced using the activation function 'relu'. Each convolutional layer is followed by a max-pooling layer (MaxPool2D) with a 2x2 pool size. By reducing the spatial dimensions of the feature maps, max-pooling captures the most pertinent data. Three further sets of max-pooling and convolutional layers with progressively larger filter sizes (64 and 128) are included in the model. The model is able to recognize hierarchical patterns and characteristics in the photos thanks to its deep architecture. A flattening layer that converts the feature maps into a one-dimensional vector comes after the convolutional layers. The flattened characteristics are then processed further by a fully connected layer (Dense) with 128 units and a 'relu' activation function.

A single neuron with a "sigmoid" activation function makes up the output layer. This is perfect for problems involving binary classification, in which the model determines whether an image is likely to contain smoke or fire. Binary cross-entropy loss and the Adam optimizer are used to construct the model. The binary cross-entropy loss function, which measures the difference between expected and actual labels, is a common loss function for binary classification, and Adam is an effective optimizer for training deep neural networks. While training the data we get an accuracy of 90.25%, while testing the model on unseen images it gives an accuracy of 96.37% .

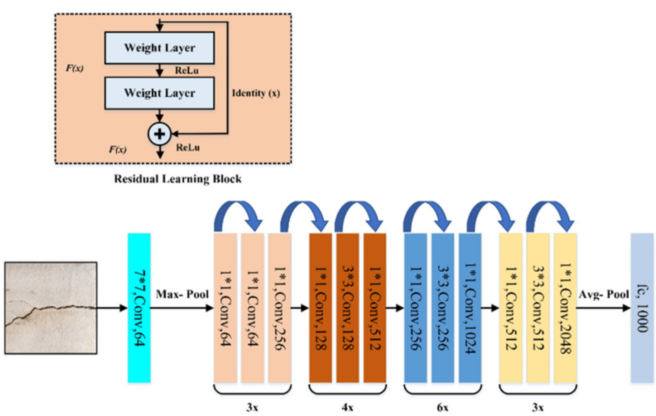


Fig. 4: Working of ResNet50 model

Keras is used in the ResNet50 model implementation to load pre-trained weights from the ImageNet dataset into the model [19] [20]. Fig. 4 shows the internal layers of this model. With its broad range of visual patterns and objects recognition, this pre-training gives the model a strong basis for feature extraction. The top (classification) layers of ResNet50 are not included since the "include_top" option is set to "False," meaning that these layers will be specially designed to meet the demands of the particular fire detection task. The next phases describes customized top layers for the base model, which is an essential modification to tackle the problem of fire and smoke detection. The output from the base model can easily be retrieved by saving the model. A layer is added that presents a method called global average pooling, which produces a fixed-length vector for every image by reducing the spatial dimensions of the feature maps. This modification is frequently used to enable classification tasks to be performed on the ResNet50 output. Afterward, a fully connected layer with 128 units is added using the expression "Dense(128, activation='relu')(x)" and an activation function of 'relu'. Processing the flattened characteristics and identifying higher-level patterns depend on this dense layer.

The output layer is defined by "Dense(1, activation='sigmoid')(x)". This layer, which consists of a single neuron and uses a 'sigmoid' activation function, determines the likelihood that an image contains smoke or fire. A rating that is nearer to 1 suggests that there is a high chance of smoke or fire. The unique top layers are smoothly linked with the main Resnet model to complete the model architecture. Interestingly, the layers in the basic model stay frozen, meaning that they won't be modified while the model is being trained. Rather, the custom top layers are where the fine-tuning is concentrated. This is a deliberate decision that makes use of the information that ResNet50 has learned from ImageNet to help it recognize features that are relevant to smoke and fire detection. The binary cross-entropy loss function and the Adam optimizer, which are common choices for binary classification problems, are used to assemble the model and train it. The binary cross-entropy loss is a crucial tool for improving the performance of the model since it measures the difference between the expected and actual labels.

While training the Resnet model we get an accuracy of 88.23%, while testing the model on unseen images it gives an accuracy of 89.25% .The model is trained using the 'fit_generator' function. Working with data generators, which manage huge datasets with minimal memory usage, is the purpose of this function. Utilized are the validation and training data that were previously generated. During training, batches of preprocessed images are produced by these generators. The whole training and validation datasets are handled during training due to settings for steps per epoch and validation steps. Model-defined callbacks are used to record the optimal model checkpoints, keep track of the training process, and, in case of need, initiate early termination. These methodology demonstrate the effectiveness of our approach in wildfire prediction.

Our work goes beyond image analysis to characterize regions that are prone to fire events on a regular basis. We are able to assess and classify areas that have had repeated fires in the past by combining the geospatial data. MODIS C61 fire data of Quebec is extracted for doing area analysis. Establishing the risk assessment methodology for early fire detection and mitigation depends heavily on this classification. These strategies are vital for forest fire prevention and minimizing the potential impact.

An essential step in early detection is the calculation of fire risk probabilities, which can be modeled mathematically:

$$P(FireRisk) = f_{risk}(A, F) \tag{3}$$

Where P(Fire Risk) is the fire risk probability, A denotes the area characterization, and F represents fire incident features. This probability guides the allocation of resources and intervention efforts.In the mitigation phase, strategies may include controlled burns, early warning systems, and public awareness campaigns. The effectiveness of these measures can be assessed using performance metrics like precision, recall, and F1-score.

V. Result and Discussions

A. Simulation setup and tools

A powerful computational infrastructure, consisting of Kaggle notebook with an GPU P100 offers disk space of 73.1GB, RAM of 29GB, and 15.7GB GPU memory, supported our research by offering the capability needed for intricate calculations. Kaggle Notebook, a flexible cloud-based environment that allowed us to develop ResNet-50 and CNN. The libraries of choice were TensorFlow (Version 2.x) and Keras (Version 2.x), which were fine-tuned to extract complex characteristics from satellite photos. QGIS 3.32.3 dominated the geospatial space, enabling us to examine and display georeferenced fire data. OpenStreetMap (OSM) standard maps were easily included into QGIS to provide a trustworthy spatial reference, which enhanced our geospatial analysis. With the aid of this extensive toolkit, we were able to carry out an extensive research that included risk assessment, deep learning, and image analysis, leading to the development of an all-encompassing strategy for managing forest fires.

B. Performance analysis

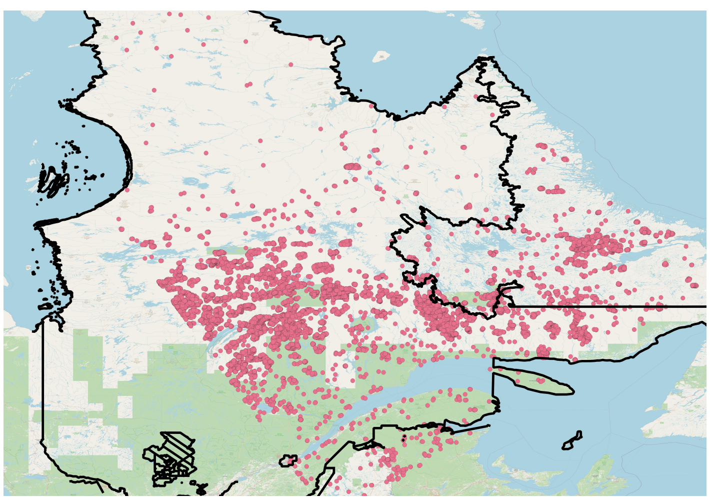
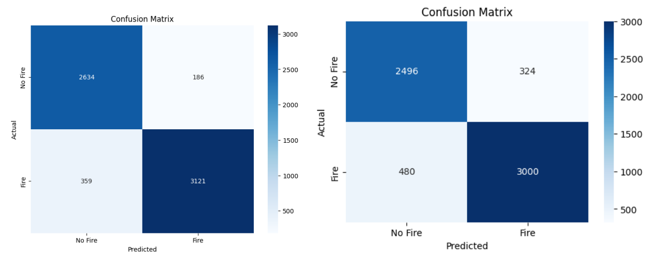


Fig. 5: Wildfire map of Quebec, Canada

Fig. 5 shows wildfire map of Quebec in QGIS, which helps in better visualisation of affected areas. The image shows that the central and southern part of the state is severely affected by this wildfire since long time. Keeping in mind this situation the government authorities should take necessary action to reduce its impact. The map is highlighted using shp file of Quebec.



(a) CNN (b) ResNet50

Fig. 6: Confusion matrix

Fig. 6a shows the confusion matrix for test images. This matrix proves the effectiveness of using DL techniques for fire detection. It shows that out of 2820 actual fire images it predicts 2496 correct and out of 3480 no fire image 3000 are predicted correctly with no fire hence it gives a good ratio of correct predictions.This means that a good number of guesses were right, which shows how strong our CNN model is. Our results strongly suggest that CNN is very good at making models for our fire data.

In parallel, Fig. 6b presents the confusion matrix for our ResNet-50 model, delivering equally good results. It shows that out of 2820 actual fire images it predicts 2634 correct and out of 3480 no fire image 3121 are predicted correctly with no fire hence it gives a good ratio of correct predictions. The output of the ResNet-50 model is very similar to that of the CNN, which shows that it is good at this task. These results support the use of deep learning models to find forest fires and set the stage for successful early response and prevention plans.

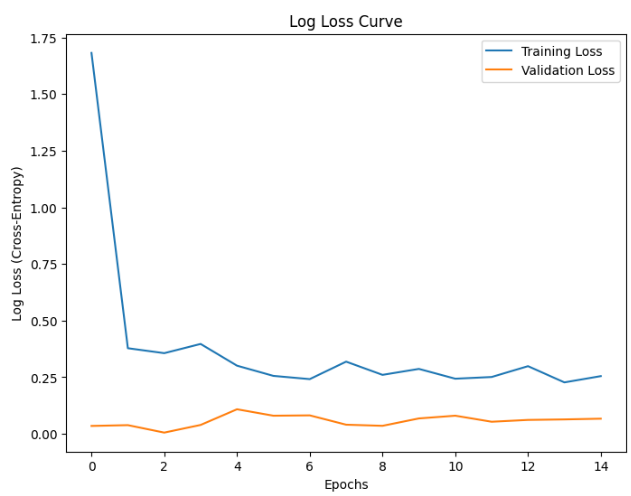


Fig. 7: Log loss curve for CNN

Fig. 7 shows the log loss (cross-entropy) curve for our CNN model, which shows how it learns over time. The initial sharp

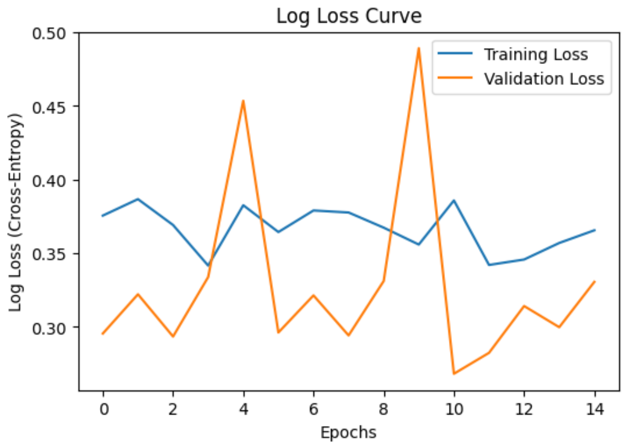


Fig. 8: Log loss curve for Resnet

drop in log loss clearly shows that the model quickly picked up new features and learned representations from the data. After that, the curve steadily goes down for both the training and testing datasets. This shows that the model can transfer what it knows about forest fire patterns. This downward trend shows that the model can make more and more sure and correct predictions. On the other hand, Fig. 8 shows that the log loss curve for the ResNet model has a more wavy shape, which means that the model is over-fitting and can't generalize well. Additionally, the ResNet model shows promise for feature extraction and complex representation capture. However, the CNN model's loss curve shows stability and consistency, which suggests that it would perform better at finding forest fires. These results show how well our DL models work and how important it is to choose the right model when trying to solve the problems of finding forest fires.

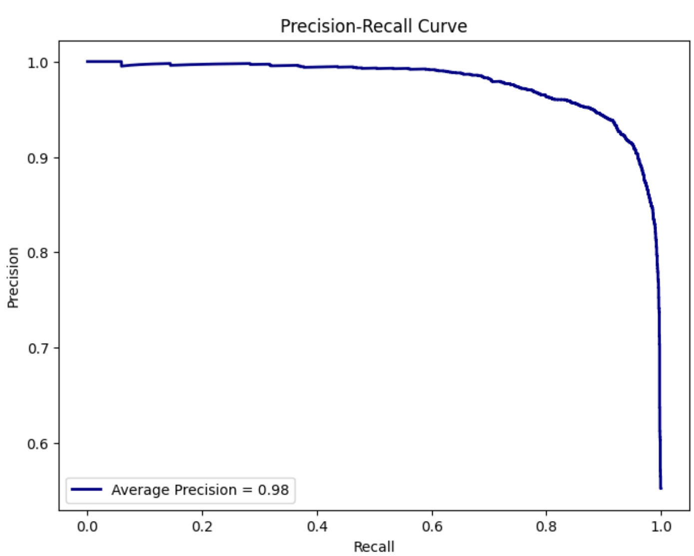


Fig. 9: Precision Curve CNN

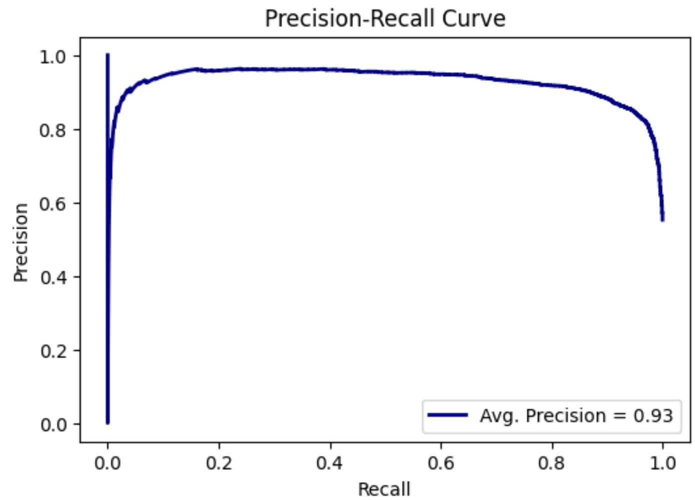


Fig. 10: Precision Curve ResNet50

Fig. 9 and Fig. 10 shows the most important part of our review. It shows how well a model can accurately predict positive classes while keeping false positives in check. The trade-off between recall and accuracy at different classification thresholds with these precision-recall curves. Looking more closely at our CNN model's accuracy-recall curve, it's clear that it knows how to get the best results for both recall and precision, with the goal of getting high numbers for both. The precision-recall graph for the ResNet model, on the other hand, is very different. It shows how well it can reduce false positives while still making accurate positive class predictions. There is, however, one feature that stands out during this comparison: a clear kink in the ResNet curve that shows a change in the model's behavior. When you put the two models next to each other, the CNN model stands out because it has a bigger area under the precision-recall curve. This means it does a better job of keeping the balance between precision and recall across different classification levels. This study shows that CNN is very good at finding forest fires, especially when it needs to accurately identify the positive class while reducing the number of fake positives. This makes it a powerful tool for real-world use.

We tested our forest fire detection models using ROC-AUC (Receiver Operating Characteristic - Area Under the Curve) measures, which gave us useful information about how well they could tell the difference between different types of fires. As the most important tool for testing binary classification models, ROC-AUC gives you a detailed picture of how well the model works at different levels of judgment. This measure is very helpful for figuring out how much the True Positive Rate (TPR) and False Positive Rate (FPR) are worth. Fig. 11 shows the ROC-AUC curve, which shows how well the CNN model can tell the difference between positive and negative samples. The path of the curve shows that the model can

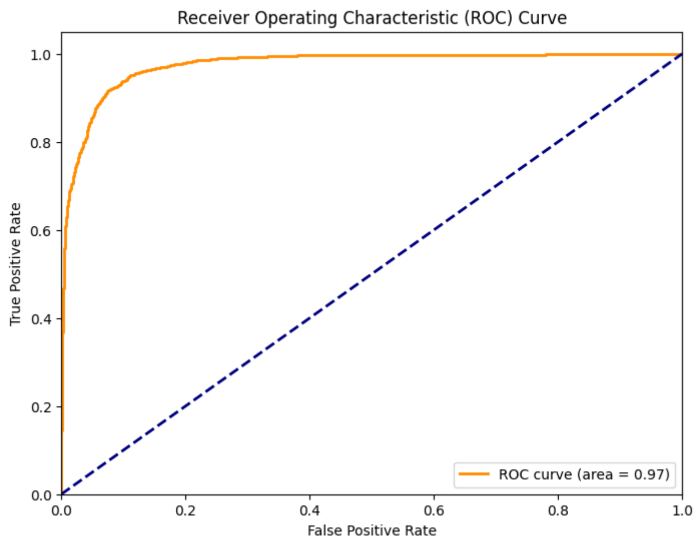


Fig. 11: ROC curve for CNN model

get a high TPR while keeping a low FPR, which shows that it works well for binary classification tasks. In this case, a bigger AUC score means that the ability to discriminate is better.

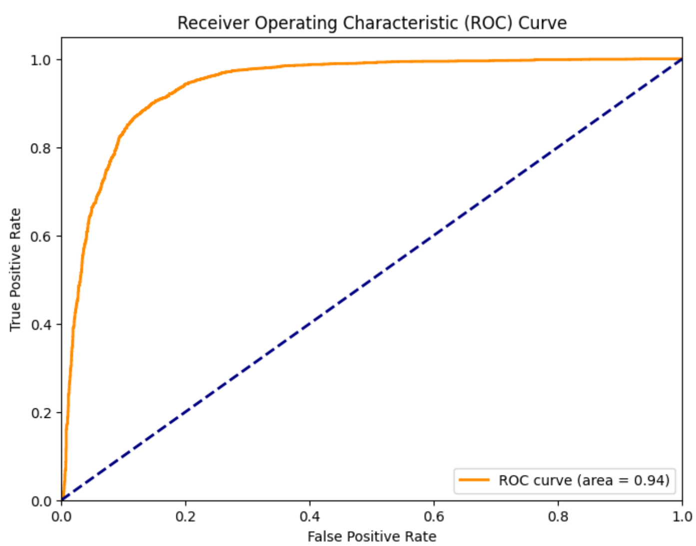


Fig. 12: ROC curve for ResNet50 model

Fig. 12 shows the ROC-AUC graph for the ResNet model, which also shows how well it sorts things into groups. The goal for both models is to get a higher ROC-AUC score, which shows how good the model is at binary classification tasks. The CNN model is better at telling the difference between classes than the other models. This is shown by its bigger AUC under the ROC curve, which shows that it can accurately tell the difference between forest fire and non-fire cases. This analysis shows how good our models are at telling the difference between things and proves that the CNN model is the best at this particular forest fire detection job. These ROC-AUC tests are very important for figuring out how well our models work, which proves that our forest fire warning system works.

VI. Conclusion

In this study, we looked into forest fire detection in a lot of detail, with a focus on how it works in the Quebec area of Canada. The main part of our study was using geotagged historical satellite data and carefully visualizing it using QGIS. It became clear how important it was to have a strong fire prediction system because forest fires are becoming more dangerous, they can damage the environment, and they can ruin lives and businesses. We acquired aerial image datasets, which we then analysed and processed to prepare them for deep learning techniques. We proposed CNN and ResNet, two powerful DL models that can automatically take features and classify them. The CNN and ResNet parts of our study, without any external hyperparameter tuning, produced interesting results. The CNN model in particular, emerged as better model in our investigation, achieving an impressive maximum accuracy rate of 96.34 percent. This exceptional accuracy underscores the potential of CNN in the domain of forest fire detection and demonstrates its proficiency in classifying images for this critical task. The significance of our research extends to its potential impact on forest fire management. By achieving high accuracy rates in early fire detection, we have the opportunity to minimize the ecological, economic, and societal repercussions of forest fires. Early detection of these incidents promises public safety and environmental preservation in addition to enabling quick response and control.

In the future, we aspire to extend the application of our proposed architecture to address various image recognition challenges. Moreover, to enhance predictive accuracy, we intend to explore transformer-based architectures. Additionally, collaboration with local authorities and communities will be helpful to ensure the seamless implementation and effectiveness of real-time detection and response strategies.

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