CSE 3506

ESSENTIALS OF DATA ANALYTICS

PROJECT REPORT

TOPIC – FIRE OBJECT DETECTION USING DEEP LEARNING

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BONAFIDE CERTIFICATE

Certified that this project report entitled "**FIRE OBJECT DETECTION USING DEEP LEARNING"** is a bona-fide work of **Jasneet Singh Bhatti (20BCE1281), Sreedutt Haridos (20BCE1460) c**arried out the "J"-Project work under my supervision and guidance for **CSE3506 – Essentials of data analytics**.

Dr. R. Rajalakshmi

SCOPE

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1. ABSTRACT

A fire gone out of control, poses a significant risk to both lives and property, as was evident during the Australian wildfires and bushfires which according to economists resulted in over A$78-88 billion in property damage and economic losses.
Traditional fire detection systems that are generally depended on a sensors ability to pick up on chemicals present in fire smoke like carbon monoxide to set off an alarm.
The drawback of utilizing sensors to detect fire is that they could result in false alarms, moreover when considering a large area like a forest, the alarm won't go off until the smoke is within sensing range, which could result in the fire spreading out of control before appropriated response from safety departments.
To tackle the above situation many deep learning-based solutions have been explored in the recent years, with appreciable results. However, these models are prone to false positives as well.
The detection of fire in images and videos is a crucial problem in surveillance, disaster management, and firefighting. Fire detection techniques based on computer vision and machine learning can be automated. The goal of this project is to develop a fire detection model that can correctly classify images as either having or not having fire in them.
The objective is to apply custom CNN based algorithms for detecting fire images, improving robustness of created models by introducing images that may induce errors, and comparing the obtained results with existing systems for fire detection.

2. LITERATURE SURVEY

[1] Applied a CNN model for classifying Fire and Non fire images taken from different UAV’s and achieved an accuracy of 76% on test data set, further performed fire segmentation using a customized U-Net architecture.

A colour-based detection algorithm along with edge detection techniques was proposed by [2]. The algorithm uses RGB colour model to detect the colour of the fire which is mainly comprehended by the intensity of the component R which is red colour. The growth of fire is detected using Sobel edge detection. Finally, a colour-based segmentation technique was applied based on the results from the first technique and second technique to identify the region of interest (ROI) of the fire. After analysing 50 different fire scenarios images, the final accuracy obtained from testing the algorithm was 93.61% and the efficiency was 80.64%.

[3] Conducted a comparative study on advance convolution neural networks for fire image detection. The models included Faster-RCNN, R–FCN, SSD, and YOLO v3. Concluded that the most accurate algorithm was based on YOLO v3, with 83.7% accuracy, detects fire the most quickly (28 FPS) and is the strongest robust.

[4] Achieved excellent results in forest fire detection and segmentation tasks. Using just 419 photos from the Corsican Fire wildfire dataset for training and dice loss as the loss function, this model attained an FM-score of 97.09% in training and 91% in testing. The experiments verified the model's great efficiency in separating wildfires in unorganised environments where they spread unchecked.

Image Enhancement techniques proposed by [5] for uniformly and non-uniformly illuminated dark images that provides high colour accuracy and better balance between the luminance and the contrast in images to improve the visual representations of digital images.

A simple system implemented by [6] consisted of an image-based fire alarm system, designed using a laptop and webcam as the main equipment. The method for using Convolutional Neural Networks (CNN) to identify fire. The system created achieved accuracy rate of 92%.

[7] Proposed a comparative study, analysing five recent vision-based fire detection system. These fire detection systems are based on flame colour detection combined with other features such as motion and area of frame. The fire detection system based on LUV colour space and hybrid transforms is proposed.

[8] Presents a review of the use of remote sensing techniques for land surface temperature (LST) estimation and its applications in land cover classification. The literature review covers several aspects related to LST estimation and its application in land cover classification, including remote sensing techniques used for LST estimation, algorithms for LST estimation, and applications of LST estimation in land cover classification

The problem with early detection of forest fires is addressed in [9], using deep transfer learning techniques applied to satellite imagery. They note that while some studies have explored the use of transfer learning in this area, few have focused specifically on satellite imagery. They highlight the potential benefits of using transfer learning for forest fire detection, including increased accuracy and efficiency, and conclude by presenting their own approach, which involves fine-tuning a pre-trained convolutional neural network on a dataset of satellite images to detect forest fires.

[10] Implemented transfer learning on pre-trained models such as VGG16, InceptionV3, and Xception to reduce the computational complexity and improve accuracy. The study showed that Xception outperforms other models with 98.72% accuracy, and using learning without forgetting (LwF) results in higher accuracy on new tasks while retaining pre-existing abilities. The proposed models outperform current state-of-the-art methods, and LwF can categorize novel and unseen datasets successfully.

3. INTRODUCTION

3.1 Background

Over the years, DL techniques have been used in several research initiatives throughout the years to address the issues associated with fire detection. The comprehensive feature map that the convolutional layers enabled us to produce played a major part in increased usage of these DL techniques. The object segmentation process was greatly aided by DL algorithms' ability to detect each pixel quickly and precisely in the image and characterise the look of items. When compared to standard machine learning models, these methods delivered better and more consistent results.

3.2 Problem Statement

An essential challenge in surveillance, disaster management, and firefighting is the detection of fire in photographs. Using computer vision and machine learning approaches, fire detection can be automated. The objective of this research is to create a fire detection model that can accurately categorise photos as either containing fire or not.

3.3 Dataset

- Combination of datasets has been taken for this study, along with additional images scraped from the web.
- Dataset links:
  https://www.kaggle.com/datasets/phylake1337/fire-dataset
  https://github.com/OlafenwaMoses/FireNET/releases/download/v1.0/fire-dataset.zip
- Dataset contains Fire and Non-Fire images for the purpose of classification.

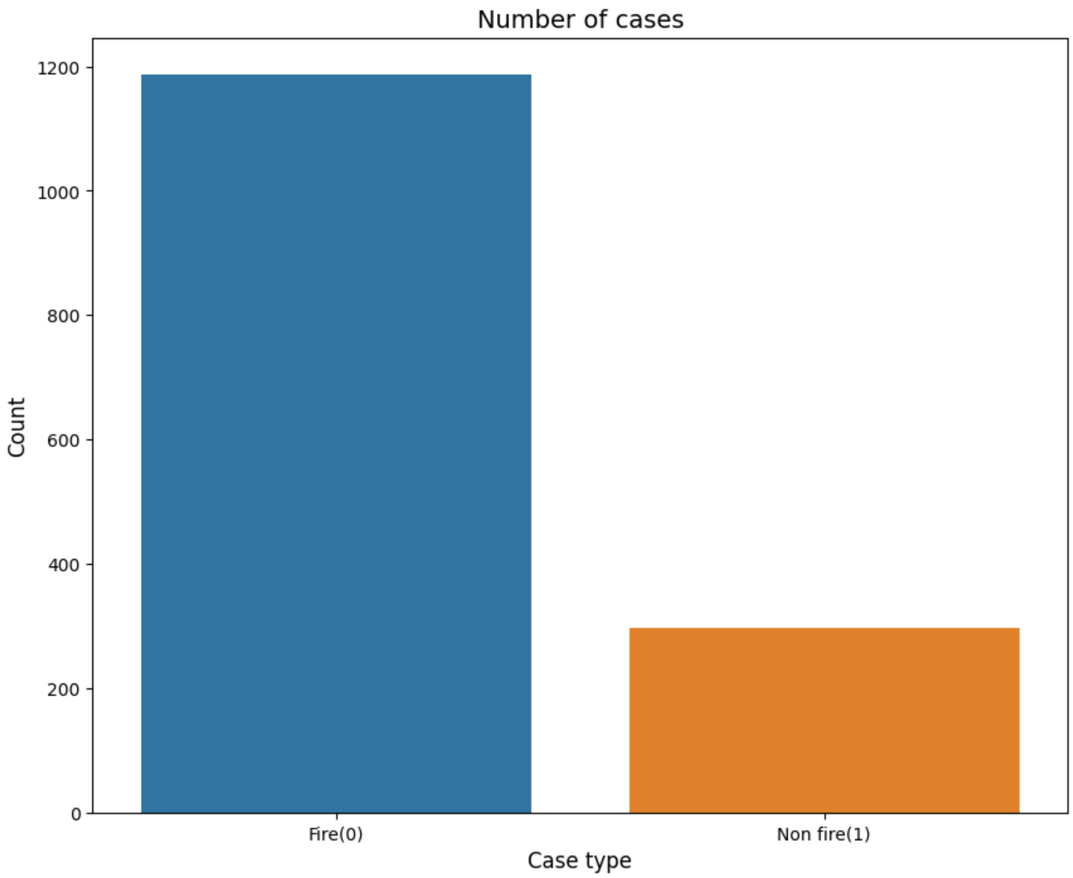
4. PROPOSED METHODOLOGY

4.1 Dataset Preparation

The photos were pre-processed using several methods before training the model. The contrast of the photos was improved using the contrast-limited adaptive The base dataset taken from Kaggle was combined with another dataset consisting of 500 fire images in different scenarios, further images that may induce errors were scraped using a python script and added to the dataset as well.

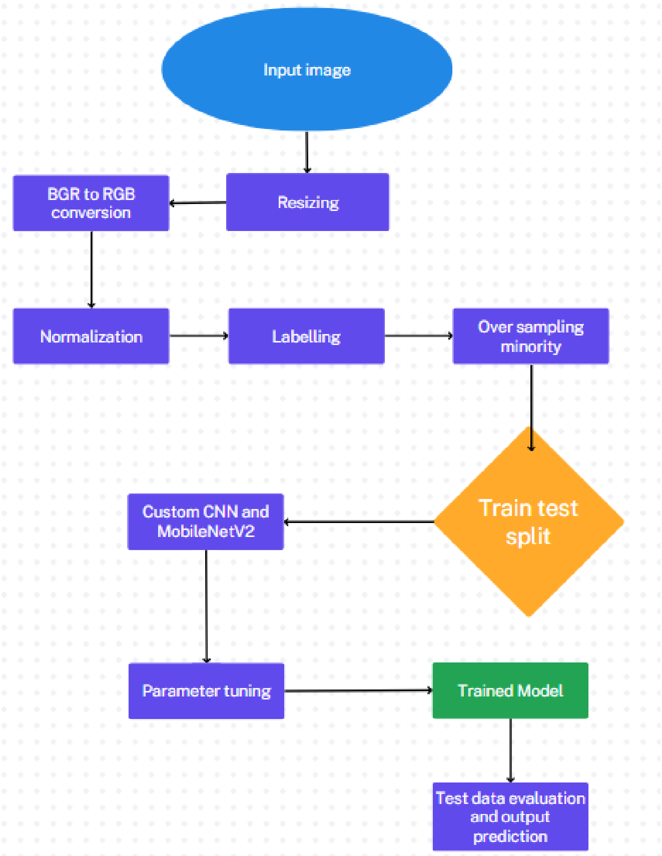
Table 1: Image distribution in the dataset

Class	Number of images
Fire	1187
Non fire	297
Total	**1483**



4.2 Pre-processing

The pre-processing included conversion of input images from BGR to RGB colour space, resizing to 224x224, normalization and labelling.
Further, since the data is skewed in favour of fire images, SMOTE is applied for over sampling the non-fire cases.



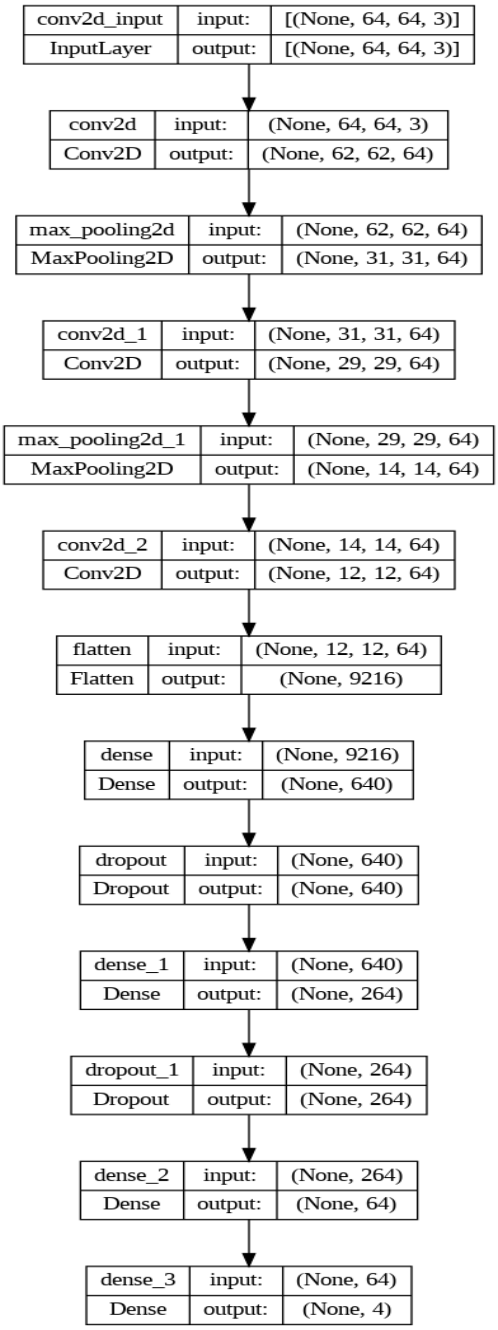
Pre-processing flow chart

Table 2: Image distribution after over sampling

Class	Number of images
Fire	1187
Non fire	1187
Total	**2334**

4.3 Network Architecture

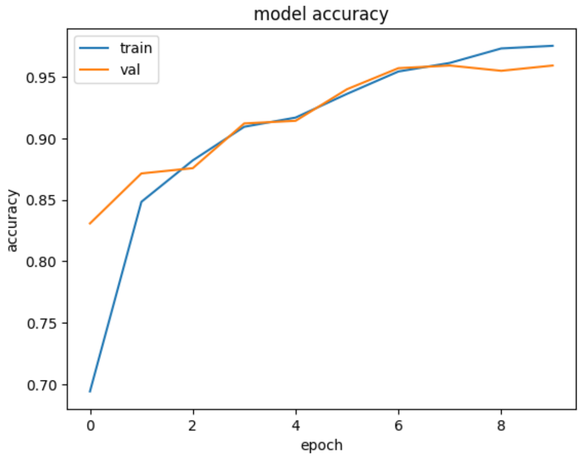
The architecture of the custom CNN is described by the image below

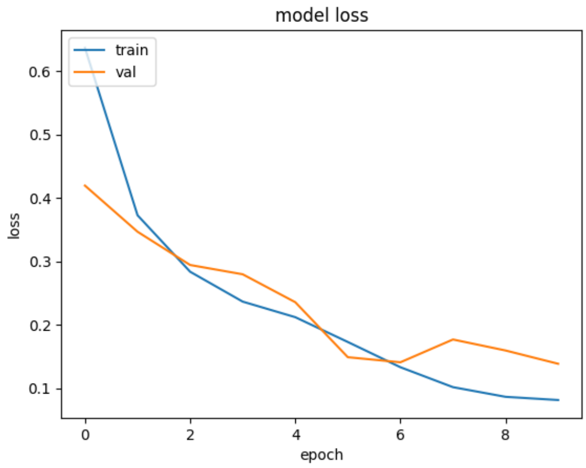


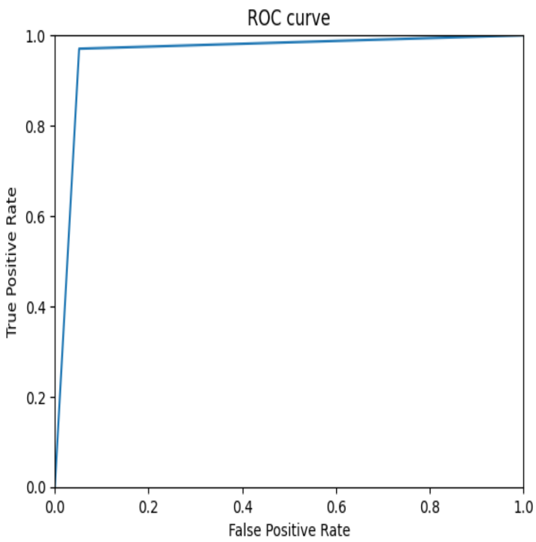
CNN architecture

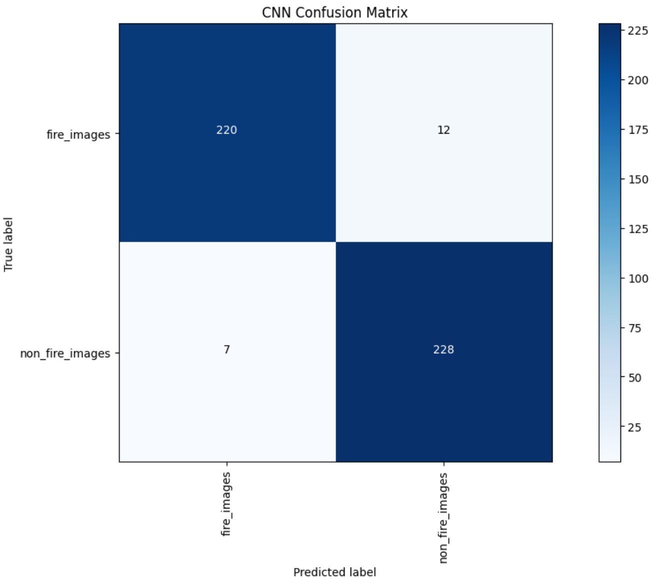
5. RESULTS AND DISCUSSION

The model achieved an accuracy of 98.93% on the test set for 50 epochs. The precision and recall for the fire class were 97% and 95%, respectively, while the precision and recall for the non-fire class were 95% and 97%, respectively and F1 score for both the classes was 96%.









The area under the roc curve is around 0.96, implying that model is extremely capable at differentiating the described classes.

6. CONCLUSION

The comparison between the models is made on the test set and is based on the results of 10 epochs.

Strategy	Dimensions	Accuracy	F1 score
CNN	64x64	95.93	96
MobileNetV2	224x224	98.07	98
ResNet50	224x224	98.5	98

The above comparison shows that the proposed CNN model can achieved results similar to transfer learning models, with the accuracy curve displayed in the previous section showing that the accuracy can still be bought up by increasing the number of epochs.

In conclusion, the proposed fire detection model based on custom CNN architecture achieved high accuracy and precision in detecting fire in images. The pre-processing techniques used in this project helped increase the accuracy of classification. The model can be further improved by using larger datasets, fine-tuning the hyperparameters of the model and exploring other applicable image processing techniques.

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