Wild Fire Detection Using CNN

Soujanya M
Department of ECE
University B D T College of Engineering
Davanagere

Prof. Hanumanthappa S N
Department of ECE
University B D T College of Engineering
Davanagere

ABSTRACT

A deep learning algorithm is developed to provide high prediction accuracy of total burned areas of specific wildfire incidents the study investigated the potential of using deep learning and specifically computer vision technologies in order to produce a classification of burn severity using forest fire areal imagery. A convolution neural network model was trained on post wildfire areal imagery of affected human structures and learned their burns severity. This will enable the video surveillance systems on forest to handle more complex situations in real world. The accuracy is based on the algorithm which we are going to use and the datasets and splitting them into train set and test set.

I. INTRODUCTION

Forests are very important things and things and that is the one of the valuable property in our globe, andwe have to protect that environmental property, since two years situations we faced covid situations very badly and also we suffered from very less amount of oxygen, the oxygen level is going to very low, we have to improve that by planting and also forest fire controlling the forest fires, here wildfires are caused from some environmental phenomena like sparks from the rock falls, volcanic eruption and ignition from humans, that leads damages like human and environmental properties and that will be reasons for soil erosion and air pollution. To prediction of forest fires is one of the toughest thing, for better and perfect accuracy we using CNN in deep learning and this involves the steps that will going through these steps ,data collection, data processing, sample library generation, sampling and re sampling, evaluation.

II. LITERATURE REVIEW

[1] Fire can be detected by using the amount of smoke. The smoke sensors are used to measure the amount of smoke from the fire, and it could be compared with a threshold value and if it is beyond that value, it is considered as a fire scenario. Using image processing, fire can be detected as soon as possible. Fixing the CCTV camera everywhere and the images from these cameras can be processed to monitor the fire. If any changes occur, it is easy to detect and extinguish the fire quickly. This system has a water extinguisher for extinguish the fire when the alarm turns on. The CCTV camera is used for recording the video of a particular spot and it is connected to a mini- computer

[2] A research study proposes a system which is a combination of using neural networks, computer vision rules, and other expert rules helps in detecting the forest fire. Different approaches are applied to build this system; visual infrared image matching, using the previous hazards memory, image processing, location, size, and geographical data. Here, infrared cameras, visual cameras, meteorological sensors are using for the collection of input data. The image processing tool is combined with the visual and infrared processing. Infrared processing is a combination of detection, oscillation, and alarm processing processes. The growing-region algorithm is used to separate the false alarms. The visual processing finds out the exact location of the visual image from the infrared analysing process. By using different algorithms, it can be detected and easily reject the false alarms. The meteorological information used to detect the humidity, temperature and other factors which affect the forest fire. So that, it is easy toestimate the possibility of fire. Using this proposed system, it can be detecting the forest fire in early stage and avoid the false detection (Begoña C. Arrue, 2000).

[3]This paper put forward an approach in real-time forest fire detection using wireless sensor network paradigm. This method can detect and forecast the fire more accurately than the other methods used in forest fire detection. Firstly, the sensor networks acquire the details about the humidity, smoke, temperature, and wind speed as these factors affect the forest fire. The sensor nodes are placed widely in the forest, and it is arranged into clusters. The sensor nodes use GPS to track their location as they can sends these location details along with the data such as measurements of temperature to the cluster head. Then, using a neural network method, the cluster header computes the weather index and then these information sends to the manager node. The wind speed is calculated by the wind sensor nodes, which are manually placed in the forest. The users get information from the manager node when an abnormal event occurs like high temperature and smoke. As well as manager node gives information about the levels of forest fire risk rate according to the weather index from different clusters. So that, users can easily find out the exact location of fire in the forest if it occurs. Also, they could protect the forest from the fire hazard due to the early detection (Liyang Yu, 2005).

[4] Deep learning and wireless sensor network can be helpful in forest fire detection. The research put forward a system using these approaches can detect the forest fire in the early stages. Using the deep learning model, the system detects the fire according to the collection of data from different sensor networks placed widely in the forest. Here, the system consists of the Internet of Things used as a main concept, moving or fixed sensors and a suitable deep

learning model. More accurately, there are several sensor nodes places within each 1 km distance and these nodes are transfer data to the internet servers through the gateways. Then this collected information is displayed in a dashboard with online network. Each node measures the values of humidity, carbon monoxide, temperature, carbon dioxide, and atmospheric pressure. These factors have a major role in the forest fire. In this method, firstly, it calculates the weather information from the weather detector located in forest and then find out the Fire weather index (FWI) using the sensor nodes with the help of deep learning algorithms and the metrics. If the FWI have value changes, the Unmanned Aerial Vehicle (UAV) helps to detect these sensor values more accurately to find the existence of fire. Also, the control tower act as a fire distinguisher to distinguish the fire (Wiame Benzekri1, 2020).

[5] This research paper, the authors propose a cost-effective fire detection using CNN from surveillance videos. This papers critically analyses the statistics of deaths due to fire. So, their focus is to propose a system that is home friendly and commercial. This paper gives us an insight of how to carefully select the data properly, how to analyse the computational complexity and detection accuracy. They use a model called Google Net for extracting the features from the images. For reducing the complexity of larger patches, they reduce dimensionality. The model is tested with two different datasets for validation purposes and results are compared. They achieved an accuracy of 93.5% on the first dataset and an 86% on the next dataset.

III. PROPOSED FRAMEWORK

The proposed framework utilizes the advantages of a convolution neural network. The CNN receives input, it is pre processed and pools them using region of proposals. Then the region-based object detection algorithm in CNN classifies those proposals into fire and non-fire in the region of interest (ROI) with the help of convolution layers. With the software specifications of using language python and bootstrap.

A. CONVOLUTION NEURAL NETWORK

Convolution neural networks are special kind of artificial neural network that can mimic the human brain activity to analyze data with supervised learning. CNN is modified multilayer perception, which means fully connected network. It consists of several layers namely, input layer, output layer and many hidden layers to make it happen. These hidden layers are convolution hence the name convolution neural networks. It offers beyond the limit abilities to perform object detection. These convolution layers use several mathematical models to critically evaluate and analyse data. Then these outputs of the previous layers are passed to the next layers. There is chance of over fitting since the network is fully connected. To avoid this situation, the CNN exploit the hierarchical pattern in the data and sort them according to their complexity from simpler to complex patterns engraved in the layers. The input is given as tensor with number of inputs x height x width x channels of input. Now the image is in an abstract form, then the layers convert this abstract image into a feature map. This is repeated layer after layer which simulates the working of brain neurons. Since it is fully connected network all the output gets filtered and combined as a single output in the output layer. The number of filters directly proportional to the feature map size.

B. ARCHITECTURE

The architecture of a Convolution neural network comprises of convolution layers. CNN is different from other object detection algorithms because of the ability to generate region of interest in the original image using image transform filters called as convolution kernels. While other algorithms take the weighted sums and connection weights to build the model. The number of feature maps generated will be equal to the number of kernels. The pixel color in the feature maps represents activation points. White pixels in the feature map are points in the original image with strong activation points. Grey pixels represent weak activation points, Black pixels represents strong negative activation points. The fire region in the original image is reddish orange so the convolution kernel changes the pixels to white. Each neuron in the convolution neural network receives an input from a restricted part of the previous layer. Each neuron in the network gives an output by executing functions in the output of previous layers. These functions are determined by the weights of the input values. A unique feature of Convolutional neural networks is that it can share the same functions on every layer. The feature extractor used in network is called AlexNet deep CNN, which is a simple application of CNN which enables easy object detection in an image. Fig. 1 depicts the simple architecture of Convolution neural networks.

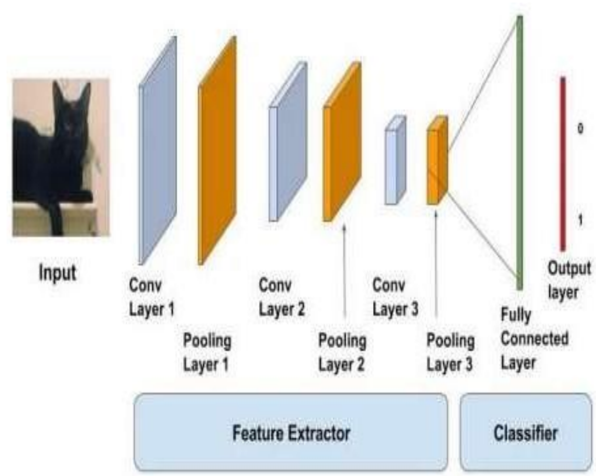


Fig 1: structure of CNN

The above figure Fig.1 represents the basic architecture of Convolution neural networks; the data is given as input, images of fire in this case. Then the layers of the network make an abstract form of the image removing all background noises and highlight the object that needs to be detected. The layers produce region of proposals that are later combined to build a machine learning model in the fully connected layers and the decision-making algorithm analyze output from layers to reach a conclusion.

IV. METHODOLOGY

In this paper, the proposed methodology consists of different stages. The stages include A. Acquisition of Dataset, B. Data Pre processing, C. Feature Extraction, D. Building model, E. Validation and testing

A .DATA COLLECTION

The Cal Fire Arc GIS network connection of the Wildfire structure identification was used to get labelled information about the burning severity of the structures. The structure's longitude, latitude, and burn severity were previously kept in tabular form, with the burn severity being labelled by human inspection at ground level. Using GIS software, the valid burn severity classifications (along with the burn rating in percentage) were then stitched along with aerial photos flown over the Campfire-affected area in Butte County. The aerial imagery was collected on December 1st and 2nd, 2018, and was taken with a precision of 4cm on the ground by Civil Air Dispatch.

B. DATA PREPROCESSING

In order to prepare the dataset for training the convolution neural network to produce the images and burn severities, several pre-processing steps were necessary. Post-processing on the aerial photographs was done using 256*256 pixel scaling. After that, numerical representations of the scaled images were created. When images are transformed into 3-D mappings, which are 2-D matrix of streams of three factors each denoting the red, green, and blue (RGB) image pixels, helped achieve this goal. In order to boost the accuracy of various machine learning approaches, the RGB values were normalised to values between 0 and 1, which range from 0-255. Because the classification was performed using a convolution neural network, the final output layer was made up of many nodes representing each of the four classes involved. As a categorical data type, each image's burn severity was recorded in a tabular format (string). As a result, This category result was transformed into a 2d matrix, each component of which denoted one of it's classes; a 1 was added per each factorisation, and a 0 was applied to the remaining components. Pre-processing began with the selection of acceptable forest fire impacting elements and the creation of ignition vector datasets as well as parameters vector information. After that, the sample libraries were gathered from the recognised IRDs and VRDs using the proper sampling methodology.

C. RE-SAMPLING OF THE DATA SET

Random oversampling is the re sampling strategy employed in this work, which randomly samples the dataset's minority classes with replacement

D. MODEL OF CLASSIFICATION

A deep convolution neural network was used to categorise post-wildfire aerial photos based on their burn intensity. The Image Net's architecture was based on Simonyan and Zisserman's VGG-19 paradigm. Until the dataset's classes are distributed equally. This would result in a collection with a total number of 90 samples, which is significantly too tiny for a deep learning method like a deep convolution neural network due to the extremely skewed dataset's lack of more than 18 samples from minority class majors. However, random under sampling could have been investigated as an additional option. RUS has been ruled out as a re sampling strategy, despite its computational efficiency, because developing a model for this inquiry using the RUS dataset would be inadequate significant classification problem. The result is a 4 segment with values ranging from 0 to 1, with each component indicating the predicted class probabilities estimated by the model. As we try to create a classification, the correctly predicted class is established by adding all these probabilities.

E. TRAINING

The Adam optimizer is also used to training set, with a computed value of 103 and loss of 105. The training error was classified leads to higher levels, and there were 100 training epochs with a dataset consisting of 16.

F. SAMPLE LIBRARY GENERATION

Due to the fact that CNN training is done under close supervision, it is necessary to build training and validation sample libraries beforehand. It was decided to use a binary classification method to classify samples in order to determine their flammability or lack thereof. Samples were given a 1 for flammability and a 0 for lack thereof. Because there are so many parameters that can be learned and estimated by the CNN, more data is needed to train it sufficiently. A straightforward random sampling technique would result in an imbalanced datasets of the model due to the small sample size. Hence, sampling design was used to enhance the sample size while maintaining an equal sample size. We calculated the amount of wildfires by the data rate to specify the amount of fire samples each year (0.8). The set of non-fire samples was used to randomly choose 49,706 training samples.

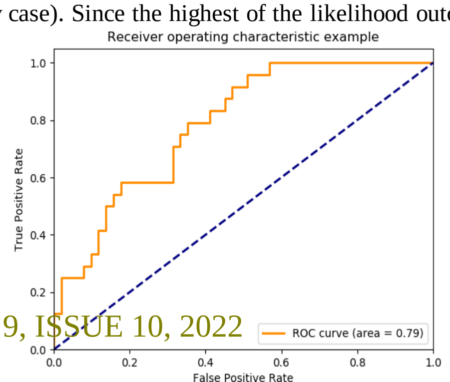
Fig 2 Video processing unit

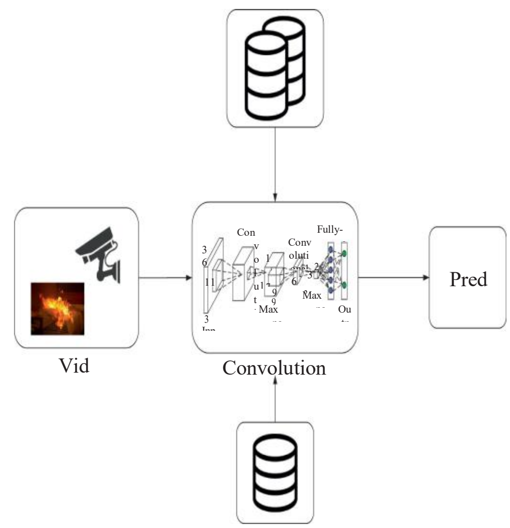
G. EVALUATION

In order to analyse the classification performance and guide the design of the classifier, the evaluation criteria are essential. Forest fire susceptibility is modelled using a two-class categorization system. For this reason, five statistical measures are used to evaluate classification capability: the overall precision, delineation, sensitivities, and positive and delineation predictive values the initials TP and TN stand for the number of samples that were correctly classified as positive or negative observations. True positives and false negatives are the number of misclassified samples. Specifically, the proportion of incorrectly categorised negative (non-fire class) observations is referred to as the sensitivity portion, whereas the proportion of correctly classified positive (fire class) portions is referred to as the sensitivity portion. In machine learning and data mining research, the ROC curve is increasingly being used to Analyze and verify the prediction models' overall performance evaluation. Rather of arbitrarily picking a threshold, it displays the tradeoffs between the TPs and FPs. This is done by plotting the percentage of patients who are able to get a TP with the percentage of patients who are not able to get one. Good classifier ROC plots rise quickly at the origin and plateau towards the maximum value of 1. One of the most basic classification methods is likely to result in an almost straight-lined graph with the rate of success at each threshold equal to one's failure rate. AUC measures the classifier's overall performance accuracy which is widely accepted as an important indicator. Accuracy near 0.5 indicates that model's predictive ability is completely random, while an AUC of 1.0 indicates a accurate prediction with no misclassification. The better the forest fire prediction model performs, the closer the AUC value is to 1. Most multiclass classification evaluation metrics are expansions of binary classification evaluation metrics. The AUC measure is produced by getting simply graphic space. To categorise a sample into one of two possible groups, we use binary classification. To put it another way, the classifier can be both correct and erroneous at the same time. Confusion matrix sums together this information.

Evaluation metric - ROC and AUC

When the TP rate is plotted opposing the FP rate, we have what is known as a receiver operating characteristic (ROC). The AUC is measured against a line down the centre of the plot, which represents the classification of all datasets are belonging to the majority class. Area under Curve is the area under the ROC curve, which is calculated as the AUC. AUC = 0.5 for a line across the centre of the plot, and AUC = 1 for a ROC that extends to the upper left corner of the plot for the perfect classifier. As a result, the AUC serves as the classifier's measurement of performance.
The test classifier must have been a one-vs.-all classifier. This indicates that in order to apply AUC to the classifier scenario, categories are chosen against all others.(somewhat analogous to the binary case). Since the highest of the likelihood outcomes is used to





select one class, this is the case for the classifier created. Consequently, each class has its own ROC curve and AUC value.

In order to offer a single evaluation statistic for all classes, the AUC results are standardized using either micro- or macro-averaging. Macro averaging does not take into the number of data in each section when calculating the AUC for each group. To calculate the AUC in micro averaging, the number of samples in each class is taken into account. The class imbalance in the dataset necessitated the use of macro-averaged AUC as a performance indicator. Misclassification of minority classes will have a greater impact on macro-averaging of the AUC because class-specific AUC values are equally weighted.

V . RESULTS

An aerial image dataset of post-wildfire human structures was used to train two convolution neural networks to classify their burn severity. On the given dataset, one classifier is trained. While the other model was trained on the same dataset augmented with ROS, because the dataset had a class imbalance. Researchers found that convolution neural networks may be used to classify the severity of post-forest fire aerial imaging pictures of human structures. It was discovered, as well, that the performance metrics of Macro-AUC and Balanced Accuracy did not improve with ROS re sampling, but rather decreased it in comparison to the baseline model. According to the findings of Buda, Maki, and Mazurowski [30],When convolution neural networks are trained on an unbalanced dataset, ROS approaches almost invariably lead to improved outcomes. Even so, the achievement differences among the ROS model and the baseline model are negligible. It's possible that these discrepancies in performance are the result of little differences that occur during the course of the training process. The ROS model may have outperformed the baseline model in other outputs of the same models with different relative performances.

VI. CONCLUSION

The scope of using video frames in the detection of fire using machine learning is challenging as well as innovative. If this system with less error rate can be implemented at a large scale like in big factories, houses, forests, it is possible to prevent damage and loss due to random fire accidents by making use of the Surveillance systems. The proposed system can be developed to more advanced system by integrating wireless sensors with CCTV for added protection and precision. The algorithm shows great promise in adapting to various environments.

REFERENCES

[1] Statistics for the 2018 California wildfire season. http://cdfdata.fire. Year=2018 for the statistics at ca.gov/incidents/incidents. On hand: Monday, June 10, 2019. Date NationalLargeIndicantsReporthttps://gacc.nifc.gov/sacc/predictive/information/National Large Incident YT . On hand: Monday, June 10, 2019.

[2] AL Sterling and BP Bryant. "California wildfires and climate change." As reported in the journal Climatic Change 87.1 (2008), pp. 231–249.

[3] Environmental Change in the Western United States: A Review by Anthony L. Sterling et al. Pages 595–604 in American Meteorological Society Bulletin, volume 84.5, 2003.

[4] The team included Dmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio Co-learning alignment and translation in a neural machine. In the arXiv preprint arXiv: 1409.0473. (2014).

[5] Kumkum Garg and Rohit Choudhry. "A stock market forecasting hybrid machine learning system." Pages 315–318 of the 39.3 (2008) issue of the World Academy of Science, Engineering and Technology

[6] "Deep residual learning for picture recognition" by Kaiming He et al. In: Computer vision and pattern recognition proceedings of the IEEE. In 2016, pages. 770–778.

[7] David Chan, Mohammad H Mahoor, and Ali Mollahosseini. "Deep neural networks are being used to get deeper in face emotion recognition." IEEE Winter Conference on Computer Vision Applications (WACV).IEEE. In 2016, pp. 1–10.

[8] "Convolution networks for images, voice, and time series" by Yann LeCun, Yoshua Bengio, and others. P. 1995 in The Handbook of Brain Theory and Neural Networks, 3361.10 (1995);Gareth James and others. A primer on statistical learning. Vol. 112. The year is 2013. Class unbalanced data: techniques and applications, by Guo Haixiang et al. Pp. 220–239 in Expert Systems with Applications 73, 2017