Forest Combustion Detection using Artificial Intelligence

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ABSTRACT
Forests are a major source of natural resources that provide both direct and indirect benefits and play a vital role in human life on earth. It is our primary responsibility to save our planet from deforestation and extreme fires. The project is aimed at firefighting areas to save wildlife, and the environment and to protect endangered species from extinction. Forest fires have extreme effect on the environment, and they also affect the future for decades. In this paper forest fire detection system was based on Convolutional Neural Network (CNN).The paper uses a set of datasets that contains many images of forest fire and normal forest images. The user takes input an image and then it is determined if the given image is an image with fire or not. In this paper, we used many convolutional layers and also added two more densenet layers for accurate output. To identify the fires in the forest we used a dataset with which we can train our model and display the results in the form of graphs. Using this paper, we discuss how to build a reliable and cost-effective machine that detects forest fires efficiently and accurately.

Keywords
Forest fires, convolutional Neural Network, Precision, Recall

1. INTRODUCTION
Each year, wildfires cause many deaths and damage to the environment and the economy. Many major wildfires can be found in history such as the Landes Forest volcanic fire of 1949 in France that claimed 82 lives and destroyed

(140,000 ha) forests the size of Berlin. But also in recent years, wildfires can still be as widespread as in 2003 in Portugal when wildfires in one of the hottest summers destroyed 10% of Portugal's total forest area (215,000 ha) and killed 18 people.

It is possible to avoid global warming by reducing CO2 emissions. Here veld fires are a factor that should not be overlooked, as 20% of the CO2 in the atmosphere comes from wildfires. Worse yet, global warming and wildfires intensify. The average increase in temperature, due to global warming, leads to an increase in extreme temperatures and prolonged drying times, which increases the risk of wildfires. An increase in the number of wildfires, however, leads to higher CO2 emissions that fuel global warming.

It is therefore very important to prevent, detect, and extinguish fires in open, cultivated country or grassland areas. Automatic wildfire fire detection systems help to detect fires early and allow fire-fighters to squeeze them out of control. In addition, such programs can be extended to a larger scale, in uninhabited districts and in the back forests, where the traditional clock hiring guards would not be visible so that almost entire forests could be rented.

Early detection of fires before they become catastrophic events is essential to prevent catastrophic fires and save lives and property. With sensors that detect fire and smoke being introduced into the interior of a house, they usually require that the fire be lit for a short time to emit large amounts of smoke and then set off an alarm. Otherwise, these machines cannot be planted in large outdoor areas, eg in the bush, or the wild. In contrast, a vision-based fire detection system captures images on cameras and detects fires faster, thus providing better fire detection in advance. This type of system is cheap and easy to install. In this work, we have proposed a vision-based fire detection system that can work with a non-stop camera. The fire detection system we developed for large forests can be attached to unmanned aerial vehicles (UAVs)/drones.

Fire-based detection has been the subject of various theoretical approaches. Color model, movement, spatial and temporal features are used primarily as fire has very distinctive features compared to other materials. Almost all of the proposed methods follow the same vision pipeline, i.e., first, find moving pixels using the background eraser and then use the color model to determine the color circuits of the fire. These regions are also analysed spatially and temporarily to detect unusual and volatile fire features. Since movement is a prominent feature, these methods only work with fixed cameras, i.e.in surveillance situations. Our work is not hindered by these obstacles. We use a powerful modern approach to in-depth learning to learn feature presentations in data and train discriminating dividers to find a hot spot. We use deep convolutional neural networks (CNN) as the basis for our learning method.

2. LITERATURE SURVEY
The problem with wildfires is that forests are often remote, deserted/neglected areas full of trees, dry and explosive wood, leaves, etc. that serve as a source of fuel. These components form a highly combustible material and represent the full context of the first ignition and serve as fuel for the later stages of fire. This is an established deficit that you are trying to rectify, used to detect forest fires early, to improve or ensure the opportunity to put them out before it grows out of control or causes any major damage.

The proposed wildfire forecasting model is based on convolutional neural networks (CNN).There are a lot of tracking systems in place that the authorities use. This includes televiewers in the form of surveillance towers or surveillance towers, antennas and surveillance satellites, as well as advanced detection and monitoring systems based on the sensor camera sensors, and numerous types of transducers or sensor combinations.

[1] Zhao, Jianhui in their paper showed a shade based on shade, after the development of GMM from test pixels and segmentation of applicant fireplaces, showing a specific example of backwood fire and later marking three types of hues including white, orange, and red. The design introduces a new feature of forest fires, for example, shading scattering, which is helpful in further planning. With different effects from a single edge, the SVM optimized for the 11 most beautiful still images is useful in filtering out artificial landscapes, It is anticipated that these changes will impact the living areas for the foreseeable future. Thus, the calculation costs are kept. The only objective, however, is that most competing and firefighting regions are followed by wind-based connections between back-to-back casings. With our different degrees of coverage and different degree, linking calculations can also separate complex fire processes, for example, one fireplace slowly breaks down into a few parts, or small flames burn in one place. An examination of the Fourier definitions of various types of fire in a short period of time is carried out using terrestrial wavelets to analyze the recurrence of fires based on the geographical location. Our approach avoids indiscriminately setting a stimulus to current FFT techniques while identifying backwood fire more accurately than methods that use wavelet conversion as they were. A total of 27 dynamic brightness is measured in SVM based on the final system, and the highlights are calculated from each 20 video frames backward. Ideally, without accuracy, the calculations obtained can generate and provide continuous warnings. Our work has been tested with a ton of real video cuts and test results have shown their expertise. However, in a fire with small areas or smoke-protected areas, there is a weak and flexible fire extinguisher, and as a result, accuracy is still low in the area. Later, we will try to behave differently in this matter, for example, to separate the smoke first, and allow fire and smoke alike.

[2] Ignacio Bosch, Luis Vergaraoutlined the woodland processing plan in their paper. The flat frame for wood fire detection is derived from the bat introduced even though we focus on handling infrared images. Every infrared image is related to a pixel frame and each pixel is connected to a target cell obtained using its azimuth and spatial arrangement. The first to measure the problem of the recognition of fixed warnings, perhaps to choose a proximity to fire is in a single goal cell when the pixel intensity in the test reaches a certain limit. If the transmission of audio transmissions is noticeable, the limit may be used to fill the pneumatic recognition (PFA), earning recognition (PD) based on the signal to commotion proportion (SNR). Captured images are adjusted from pixel to pixel. A fabricated plot based on infrared image processing enables early detection of any fire hazard. To determine the proximity or absence of fire, the calculations use a combination of various indicators that are prominent predictors of a real fire, such as stability and increase. The results of speculation and down-to-earth activists are adjusting to control the framework related to the possibilities of counterfeit awareness. Under movement to commotion proportion (SNR), we also calculate probability of discovery (PD). We can use this opportunity to understand more about infrared foundation clamor to expand SNR using the commotion index. The tested level can be deducted from the test pixel, thus improving the SNR. Note that when we develop an SNR we show signs of PD development in a particular PFA. Using infrared imaging processing, the fire detection system can detect problems prior to the occurrence of fire. To determine the proximity or non-occurrence of a fire, the proposed statistics use a combination of different identifiers that distort the various surprises of the real fire, such as certainty and magnitude. The results of the pragmatic reconsideration and reconstruction are presented to familiarize the control of the potential for a false alarm alert (PFA). The probability of receiving (PD) signal reliance on commotion proportion is also assessed.

[3] Zope, Vidya discussed thatFor the earth's ecological balance, forests are one of the most important resources, are a natural home for wildlife, and forest products are essential to our lives in many direct and indirect ways. But wildfires can wreak havoc on sites and many other resources such as buildings, human life, and wildlife in very large numbers. During a wildfire, acres of land are destroyed, as everything in its path is destroyed. Wildfires destroy homes, animals, trees and plants, wildlife, and plants. The effects of wildfires are many and widespread.It has a significant impact on the economy, environment, values , and social well-being in rural areas. A number of factors contribute to the development of wildfires, such as humidity, temperature, pressure, and soil moisture, among others. In this prediction forest fires by machine learning are used to monitor a particular area and to adapt to climate change using different sensors. The Wildfire Prediction System monitors and records changes in climate limits and predicts forest fires based on real-time data, thus avoiding significant losses due to forest fires.

[4] Anshori, Mochammad discussed that to prevent forest fires, predictions should be made to detect flammable ground areas based on sensitive weather conditions, as a result of these safety measures, the fire will spread less quickly after it has been put out. The climatic conditions used in the study predict the areas of land that will be affected by forest fires such as temperature, wind, humidity, and rainfall. The study was conducted using Extreme Learning Machines (ELMs) and a neural network. To improve the performance of the ELM method, in this study a few experiments will be performed so that the resulting predictions are better.

[5]Kinaneva, Diyanaused the Aerial Vehicles (UAVs) method in their paper. AVs constantly monitor the most affected areas or the most frequent areas of fire. They do this by capturing videos with the help of drones and still images. They have compared drone-adjusted drones with rotatory-wing drones and by comparing them we can see the best. Rotary-wing drones have many aids over fixed-wing drones. In the end, they combine two types of drones to find a solution. This model detects if the fire is false. The AI used in this model is Neural Networks which is an in-depth learning method. This paper did not improve any model but suggested the actual implementation of modeling. They did not improve this due to a lack of equipment and financial problems purchasing equipment.

[6] Hamadeh, Nizar discussed that Lebanon is considered to be a gate facing east and west, with an area of 10452 sqkm. Tourists from all over the world visit it because of its position. Moreover, it is rich of caves, and the mountains are covered with various trees. The cedars and pines exist in Lebanon since ancient times. However, Lebanon has always been in danger of losing its green fields and mountains. Forest fires have caused the decline of many green hectares over the years. This paper examines the effects of weather data: relative humidity, temperature, daily rainfall and wind speed at the risk of wild fires in Lebanon. These effects compel the familiarity with certain techniques that can help predict fires and thus provide greater scope to their emergence. Artificial

Neural Networks were used for this purpose. The 2012 climate data gathered in North Lebanon, Kfarchakhna station is taken for reading. We have studied effects on both the number of neurons in the encrypted layer as well as the training methods for network performance and the mean error square. That is an indication of how effective a community is at accepting predictive decisions.

[7]Zhang, Qi-xingused Faster R-CNN to detect wild forest smoke in their paper. The feature removal process is done in the form of traditional video smoke detection. Wildland forest fires affect the natural environment and the globe. the ground-based fire detection system can detect fire easily and quickly.Using the video as evidence, we can analyze between two types of fire detection -1. Discovery of smoke, 2. Fire detectionThe smoke produced by wildfires can be seen in front of the flames. But by using the smoke detection video we can get more attention to the forest Fire alarm adaption.

Smoke Pictures: Exhaust fumes are fully based on movement or light threshold light. It is very difficult to identify thresholds due to changes in smoke speed as well natural light. To properly detect smoke, we need to take some green smoke videos.For example, we should take a green smoke frame with a back.The smoke from burning bushes is gray. Accordingly, the R, G, and B components of forest smoke match the RGB color space quite closely.Detecting smoke is much easier when the background is green. In a smokeless environment, the G-section is higher than R and B. In a smoky environment, the G-section gradually approaches the R and B growing segments.

Acquisition using Faster R-CNN: Many computer vision functions are based on deep convolutional neural networks(D-CNN). Fast R-CNN can only mean that the system contains CNN features. By using Faster R-CNN we can easily detect smoke and there is no need to remove features that can use the real image as a whole network installation without pre-processing or blocking partitions. Smoke images from real forest fires can be captured using R-CNN’s fast paced smoke detection site. We have to train R-CNN rapid forest detection models in the background smoke + forest data and model forest data databases.

As a final conclusion, we can say that, in this study, faster R-CNN was used in order to detect forest smoke.The difference between real smoke and simulation smoke allows us to create artificial images of forest smoke.

[8]Ghuge, Dr NN discussed that this paper uses an Arduino-based wireless network to detect forest fires. Forest fires can be natural or man-made. Nevertheless, they are spread across the globe. In this detection system, the system detects fire detection with sensory assistance and transmits information to the fire department. It can send an alert message to a server with the help of an MCU node where the fire is detected. The GPS module is used in this program to send alert messages. This system measurestemperature, threshold temperature and humidity. When the temperature reachesthe threshold value, a notification is sent. Testing is conducted at various locations of forest for better results.

[9]Southry, s. sree discussed in this context that the method used for the identification of forest fires is based on the SMICA algorithm. It is a Supervised Multi-Model Image Classification Algorithm. This Algorithm is used to eliminate noise in the input image by preprocessing and the quality of the picture is increased. Another detection technique used is CNN. Fires in the forest can be detected earlier using CNN than the above mentioned method because it identifies fire by eliminating non fire pixels.

Another Algorithm used is the “Infrared Channel Gradient”.In this technique, fire is detected by identifying temperature warping (the twisting of something out of its natural or normal shape or condition). Forest monitoring systems gather data about the forest environment such as forest temperature, humidity, and threshold, and also monitor whether they are suitable conditions for animals. To detect temperature, a thermal image camera is used. All these conditions are incorporated into the datasets that we use as inputs.

Materials and methods: Nowadays most forests are affected by human activities. Some of the reasons are urbanization and overpopulation which lead to outbursts of forest regions. Forest fire is generally a natural hazard to the environment and disturbs the atmosphere and also affects humans.Satellite imagery gives fire management and damage control tools for observing areas with burns. The satellite image is compared with the images from the dataset that is provided. SMICA Algorithm helps in minimizing the wildfire very fast. So forestry services can use this algorithm. With this algorithm, threshold values act as the main component of image processing. In this image processing method, steps are 1.Image enhancement, 2.Image segmentation, 3. Feature extraction, 4. SMICA algorithm applying this method has better efficiency and is also very easy to implement, and is also less complex. This method produces very high spatial resolution and quality image data. SMICA's accuracy, sensitivity, and specificity are superior to any other conventional system.

[10] Wang, Yuanbin, Langfei Dang, and JieyingRen discussed in their paper that for detecting fire automatically in the forest, a forest fire image recognition method based on a convolutional neural network(CNN) is used in this paper. In general, there are two types of algorithms to detect fire-traditional based and CNN-based.Due to blindness and randomness in selection, traditional image detection has a high probability of producing false positives. Whereas CNN is directly applied so, if the training we provide for CNN is not accurate, the recognition rate will be hugely affected.Using conventional image processing methods and CNN techniques, an approach called pooling is developed in response to the aforementioned problems. These characteristics can be learned by splitting up the fire-affected area into smaller areas. During the same time, the disadvantages of the traditional method are avoided and the non-valid features are avoided in CNN. Studies show that CNNs based on adaptive pooling perform better and are more widely accepted. The flame area is extracted depending on color so that the non-flame area is reduced and also shape and text are intensified.

3. METHODOLOGY

Deep learning networks tend to differ in depth from shallow neural networks. A neuronal network consisting of multiple hidden layers is generally defined as a neural network. Convolutional neural networks resemble neural networks. They are made of neurons with weights and prejudices that can be learned.The entire network expresses only one distinguishable score function. However, the convolutional neural network is typically defined by the type of hidden layers it uses, such as convolution, fully connected, normalization, and pooling layers. Using neural networks for image pattern recognition works well for small images that are single-layered and consist of simple shapes.However, the use of completely connected neural networks in images with high resolution and three color channels would lead to a large number of parameters that could be formed. As a result of the increased amount of parameters, the model will probably be prone to overfit.

The network of convolutional neurons has its neurons arranged in a structure in three dimensions: width, height, and depth. Instead of focusing on one pixel at a time, convolutional network uses square pixel fixes and passes them through a filter, called kernel. The aim of the process is to turn the image into a form that is easier to process, without missing features that are essential for prediction. As a result, CNN is used instead of other neural networks.

The proposed design improves fire detection accuracy and computer complexity just as it reduces the number of counterfeit instructions compared to advanced fire detection systems. Therefore, our plan is becoming more and more reasonable about the location of premature fire during testing to avoid major fire disturbances. The system used in the model is composed of image processing. For this, we have Convolution Neural Networks (CNNs). In neural systems, the Convolution neural system (ConvNets or CNNs) is one of the basic classes for creating visual information, and image settings. Object localization, facial recognition, etc., is one of the areas where CNN is used extensively.

Image processing -Assigning pixels to a photograph in subtle categories or classes.Image editing is the process of numbering pictures. To do like that, you need to configure your PC. Preparation is indispensable for a successful collection. Separation techniques have been developed through research into pattern recognition. Image layout is a learned learning problem: describe the many target classes (things you can distinguish from pictures), and train the model to remember them using the illustrated model pictures. The original PC vision models relied on the knowledge of green pixels as a contribution to the model. In any case, the information in the green pixels alone does not provide a stable exposure to compile the bulk of the article as captured in the image. The nature of the article, the background of the object, the ambient light, the camera point, and the focus of the camera can all bring the flexibility of green pixel information; these splits are large enough that they cannot be corrected by taking medium-weight points with pixel RGB values.

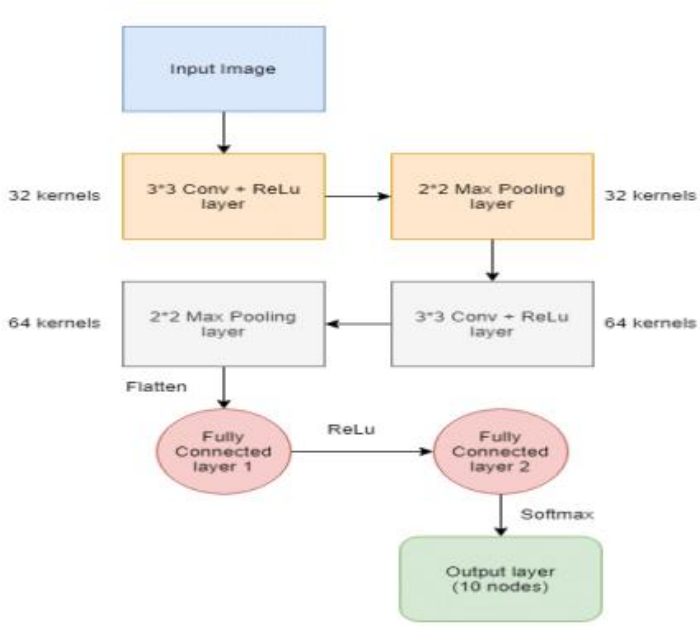

Figure 1: Flowchart showing the process of CNN.

We have considered a few network structures for this project, in terms of several parameters and normal operation. Almost all CNN structures follow the same design patterns using sequential convolutional layers and reducing sample size while increasing the number of features as shown in figure 1. So our test method studies the individual properties of each method.

4. RESULTS

Dataset Collection

The dataset is collected from kaggle.com.

The data set is split into 2 folders, the fireimages folder contains 755 outdoor-fire images, the other is non-fireimages that contain 244 forest images without fire.

```
['fire_images', 'non_fire_images']
2
Number of images with fire : 755
Number of images without fire : 244
fire_images
non_fire_images
```

Figure 2: Labelled dataset

Reshaping the images

Reshaping is done for our dataset to ensure that all the images are in the same size, same dimension, and same color mode. In this project dimension of the image is 32x32 whereas the color mode is in grayscale after reshaping. Before reshaping, all images are in RGB format and every image has different dimensions. The reshape() functionality of the NumPy library is used to successfully reshape.

Training and Testing accuracy

```
Epoch 95/100
20/20 [==============================] - 10s 505ms/step - loss: 0.1245 - acc: 0.9463 - val_loss: 0.1934 - val_acc: 0.9371
Epoch 96/100
20/20 [==============================] - 8s 421ms/step - loss: 0.1398 - acc: 0.9494 - val_loss: 0.2109 - val_acc: 0.9308
Epoch 97/100
20/20 [==============================] - 10s 500ms/step - loss: 0.0886 - acc: 0.9621 - val_loss: 0.3259 - val_acc: 0.8994
Epoch 98/100
20/20 [==============================] - 10s 479ms/step - loss: 0.1312 - acc: 0.9526 - val_loss: 0.2794 - val_acc: 0.9119
Epoch 99/100
20/20 [==============================] - 9s 444ms/step - loss: 0.1241 - acc: 0.9463 - val_loss: 0.2520 - val_acc: 0.9182
Epoch 100/100
20/20 [==============================] - 9s 452ms/step - loss: 0.1405 - acc: 0.9431 - val_loss: 0.2327 - val_acc: 0.9182
```

Figure 3: Training and Testing data after 100 iterations

After the data set has been iterated for 100 times training accuracy, training loss, testing accuracy, testing loss can be observed in Figure 3.

For more clarity we can plot graphs for training vs. testing accuracy and training vs. testing loss. We can observe that in Figure 4, Figure 5 as shown below.

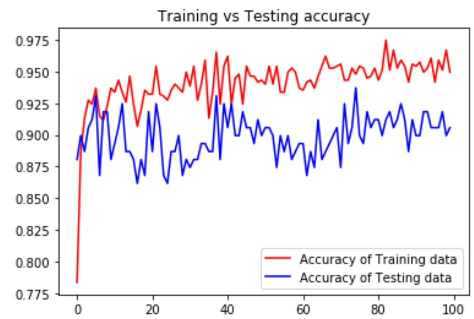

Figure 4: Training vs. Testing accuracy graph.

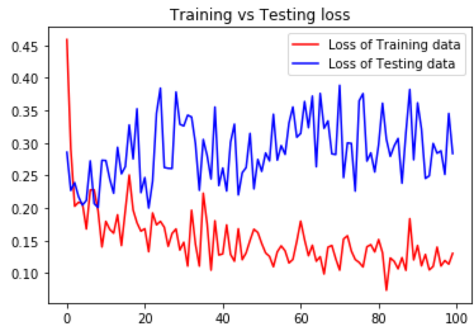

Figure 5: Training vs. Testing loss graph

Classification report

A classification report consists of precision, recall, f1-score and support which interprets performance measure.

	precision	recall	f1-score	support
0	0.91	0.99	0.95	117
1	0.97	0.71	0.82	42
accuracy			0.92	159
macro avg	0.94	0.85	0.88	159
weighted avg	0.92	0.92	0.91	159

Figure 6: Classification report

The above classification report has 2 classes. Class 0 for non-fire images and class 1 for fire images. Precision, recall ,f1-score and support for each class is calculated here.

Precision may be defined as the ratio between the correctly predicted positive observations and the total forecast of positive observations.

Precision = TP/TP+FP.

Recall refers to the relationship between correctly anticipated positive observations and all observations in the real class.

Recall = TP/TP+FN.

F1-score is the weighted mean of precision and recall.

F1-score = 2*(Recall * Precision) / (Recall + Precision).

Support is actually the number of actual occurrences of the class in the specific dataset.

Support for class 0 = TP+FN.

Support for class 1 = FP+TN.

Accuracy is the ratio between the correctly predicted observation and the overall observation.

Accuracy = TP+TN / TP+TN+FP+FN.

Macro average is the arithmetic mean of class 0 and class 1 values. For example in figure 6 macro averaged F1-score = 0.95+0.82 / 2 = 0.88.

Weighted average is calculated by taking mean of class 0 and class 1 while considering each class's support. Let us see the weighted average of F1-score in Figure 6 = 0.95*(117/159) + 0.82*(42/159) = 0.91.

In the above formulas TP refers to True positives, TN refers to True negatives, FP refers to False positives and FN refers to False negatives.

Testing the algorithm

We test the algorithm with various inputs and see its accuracy. In figure 7, an image with fire is given as input and the output is displayed as a fire image with an accuracy of 90%. In figure

8, an image without any fire is given and the output is displayed as a nonfire image with an accuracy of 91%. In figure 9, an image with fire is given as input and the output is a fire image with an accuracy of 88%. It does not matter whether the input image may be from the dataset or outside the dataset. In the output, the prediction of input image class with the class of first 10 images in the dataset is displayed accordingly.

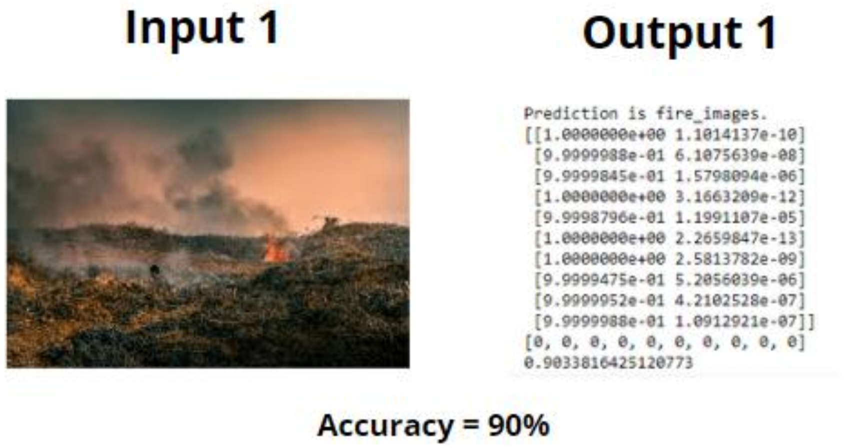

Figure 7: Input and output of first image with its accuracy.

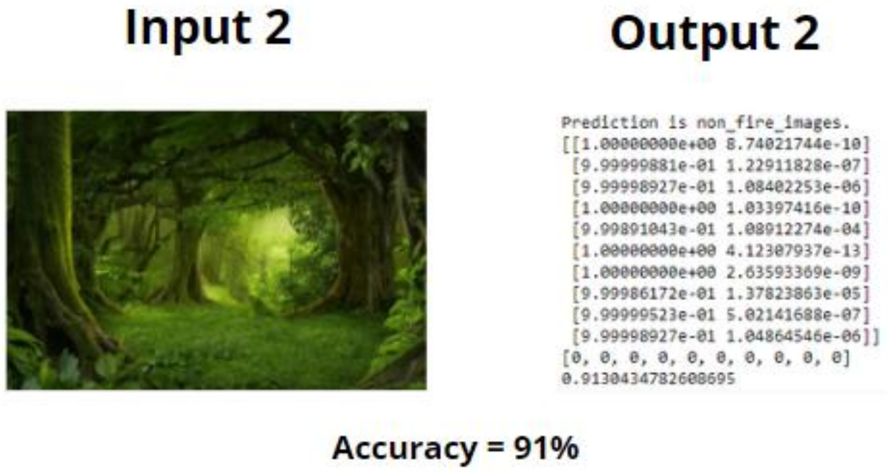

Figure 8: Input and output of second image with its accuracy

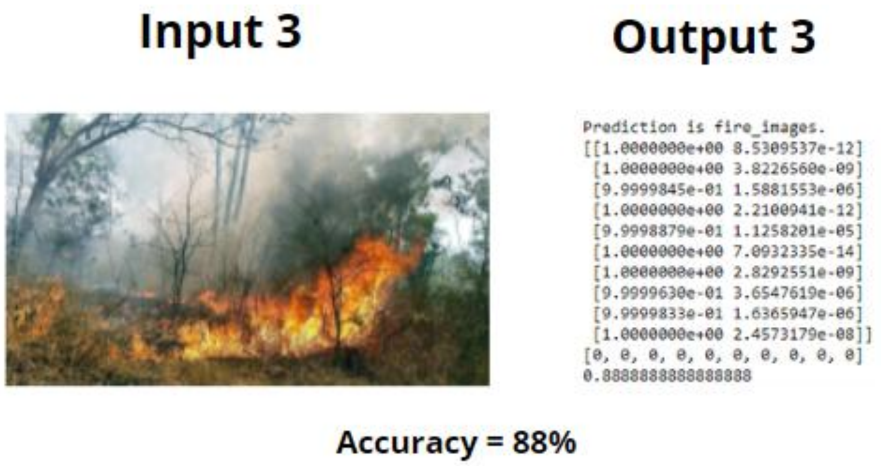

Figure 9: Input and output of third image with its accuracy

5. CONCLUSION

To answer the stated research questions, a test setup was designed, consisting of two separate data sets and a few tested network structures. During testing, many network structures were altered, trained, and operated. In the first phase of the study, two different methods were tested, the RGB input and the thermal input, and the second in a multimodal method of fire detection. In addition, comparisons of our approach with the basics are explored. The tests will conclude by looking at the first question, namely:

Can CNN's multimodal dual-division component be able to surpass previous approaches that are explicitly based on color values and temporary information on fire in terms of acquisition values?

With CNN one broadcast based on RGB images, 97% accuracy and 2% false positives were recorded. Previous methods measure the accuracy level between 83 and 98. However, because there is no reference database with the right quality or size, previously presented methods and ours remain unclear.

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