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ENRICHING FIRE DETECTION THROUGH MULTI- CLASSIFIER AND DEEP LEARNING MODEL

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ABSTRACT

Fire is one of the most destructive forces that have been a double edged sword, while it is very useful and generates energy when controlled in an effective manner, it can be quite deadly if left unchecked. The fire is combustion and a conversion and release of energy which is violent and has the ability to unleash massive amounts of destruction. This is highly undesirable circumstance that could lead to a potentially catastrophic occurrence. It has been evident in the recent years with the large number of devastating wildfires that caused a large scale loss of life and property, a large number of species of flora and fauna were extinct which one of the most deadly occurrences. The main problem is the lack of an effective and useful fire detection approach. Therefore, this research article defines an effective multi-classifier approach for fire detection that identifies the color of the fire, shape of the fire and the movement of the fire, along with the detection of smoke by using the convolution neural network. This approach has been one of the most effective techniques for the fire detection which is evident through the extensive experimental results that signify the superiority of the proposed multi-classifier fire and smoke detection approach.

KEYWORDS— *Convolution neural network, Multi-classifier, Image Morphology, Temporal effect*

I. INTRODUCTION

Fire safety seems to have become a primary priority in our current lifestyles, though there are still fire risks that may result in significant property and personal loss. As a consequence, the use of a fire suppression system was essential in both preparedness and response to the fire. The main purpose of both automatic fire detection solutions would be to identify a fire, appropriately notify and transmit messages to inhabitants, and to consult and provide knowledge among first emergency personnel. The precise conditions – including the norm of the geographic region in issue – decide how these aims are achieved.

Across the other end, detection systems are not revolutionary; they have been available for quite long period of time. In the early 1800s, many of the earliest alarms was created. Dual fire alarm systems, one with a telegraphic key and another with a lever, made up the mechanism. If a fire was found in a home or business, someone would have had to approach inside one of the devices and crank the lever to issue a warning to a neighboring alarm station. The signal would be sent to a coordinator at the facility, who would then notify the fire brigade for help. It was a multi-phased procedure that took a long time. As technology progressed ever since, the fire detection system has improved as well.

Fire alarm systems have traditionally been regarded as among the most major components in everyday life. In the long term, it will be among the main objectives of smart home control technology. A fire alarm system has components that operate with each other to recognize and alert the user using audible and visual ways when smoke, fire, or other risks develop. It may also call the emergency services to have all of the fire detection systems in the area monitored. That is the situation as it is right now. A fire alarm system is amongst the most prevalent systems that must be installed in every home and business in various countries. The technology can help homeowners be notified of a potential fire and receive advance notice.

The technology must be able to summon emergency services and contacts right away, cutting down on the time it requires for the fire department to respond. It is also possible that false fire alarms will be reduced as a result of this. This is accomplished by pinpointing the particular problem in the event of a malfunction, which can drastically limit fire damage to structures. Unlike other things, fire has a vibrant structure and is a dramatic yet uncommon optical sight.

Because of the recurring form and size fluctuations, computational vision-based fire detection systems depend on multi-feature-based techniques. The goal of such techniques is to identify a combination of traits that, when seen together, rule out fire as a probable cause. To mention a few low-level properties of fire, consider color, velocity, shape, progression, flaring, and smoke patterns. Spectral, geographical, and temporal factors are frequently utilized to identify fire zones in addition to these defining criteria.

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The Literature Survey section of this research paper examines previous work. Section 3 delves into the approach in depth, while section 4 focuses on the outcomes evaluation. Finally, Section 5 brings this report to a close and gives some hints for future research.

II. LITERATURE SURVEY

For surveillance footage, K. Muhammad et al. [1] offer a cost-effective fire detection CNN architecture. The framework is depending on the GoogleNet architecture and has been fine-tuned to reduce computing complexity and improve detection accuracy. Experiments show that the proposed architecture outperforms both existing hand-crafted features-based fire detection methods and the AlexNet architecture-based fire detection methods. In comparison to state-of-the-art fire detection systems, the suggested framework strikes a balance between fire detection accuracy and computing complexity, as well as reducing the frequency of false alarms. Therefore, the presented approach is better suited for early flame detection during monitoring to avert massive fire disasters.

J. Widodo et al. estimated backscattering using ALOS-2 PALSAR-2 horizontal-horizontal polarisation data and simulated backscattering using an impedance model in this study. Mac Pearson's correlation coefficient was used to fit this model. The correlation between simulation backscattering using an impedance model and simulation using ALOS-2 data is strong, at 0.8, with a coefficient determinant of 0.6 and a root mean square error of 1.4. It means that utilizing ALOS-2 data, the observation of a peatland risk fire zone was successful [2]. A dry peat area with a low dielectric constant is illustrated by the ALOS backscattering coefficient. The hazard of a peat fire is linked to places with dry peat and a deep groundwater table. Because of the cross-checking in each other, the combination of the novel impedance model technique and DInSAR methods, as well as other research advances, provides an advantage in the form of correct analysis findings.

G. Xu et al. propose an end-to-end amenable structure for smoke detection that depends on two state-of-the-art fast detectors, the single-shot multi-box detector (SSD) and the multi-scale brine convolutional neural network (MSCNN), and uses annotated synthetic smoke photos. To adapt a detector model that has been trained on synthetic smoke photos to real-world circumstances, an adversarial training approach is utilized [3]. To merge pose assessment and unmasking at the same level utilizing convolutional layers, a set of convolutional branches are introduced to chase the attribute layers in the fast detector for domain adaption. A category score is assigned to each projected box, indicating the chance that the box belongs to one of the two categories: smoke or non-smoke. The domain branch forecasts domain category scores, which reflect the likelihood that a given box corresponds to one of two domain categories (synthesis or reality).

Traditional techniques have trouble distinguishing thin and microscopic smoke in time because smoke is overlaid on the backdrop and has a diversity of morphologies during the rising and expanding phases. LBP-TOP+SVM, for example, is a common technique for splitting smoke images and identifying the cumulative motions of these blocks [4]. S. Luo et al. presented DNN, which is superior to previous techniques for examining smoke form features and morphological changes. This study also employs the partitioning strategy, which reduces network complexity while improving detection accuracy. Furthermore, movies are compressed into images, resulting in a smaller dynamic characteristic network. Finally, the two-stage structure is useful for finding thin and minor smoke.

Z. Lin et al. developed an active fire-detection technique that might be utilized with data from China's FengYun-2G geostationary satellite [5]. There have been several active fire-detection algorithms established in the past, but only a few are intended for geostationary data and even fewer for Chinese satellite data. FengYun-2G is a functioning satellite that delivers 5-km spatial resolution data to researchers every hour. High temporal aspiration and time series analysis helps characterize pixels and prevent inaccuracies originating by coarse spatial resolution since the spatial analysis approach helps remove many unrelated pixels. It's critical to fully realize the possibilities of time-series scanning. Data preparation, geographical analysis, and temporal scanning are the three primary processes of the proposed approach. A universal approach for processing full-disk pictures is presented, which would substantially improve the efficiency of subsequent calculations, particularly in studies where the attention may be centered on specific local locations. During the spatial analysis, prospective fire tests are used in conjunction with a combination of fixed and dynamic criteria to reject non-fire pixels to the greatest degree possible.

To address the advanced forest fire smoke identification complication, Y. Cao et al. present a new awareness intensified bidirectional LSTM network (ABi-LSTM). The authors explore the spatiotemporal representation of a smoke candidate patch utilizing a CNN and a bidirectional long short-term memory network in both forward and backward time. This is the first study to use an attention mechanism to recognize forest fire smoke from video. In the presented implementation, a soft attention technique is utilized to automatically emphasize motion particulars in the temporal domain, allowing an attention network to self-adaptively focus on discriminative frames [6]. To amplify the experiment's dependability, the authors create increasingly difficult forest fire smoke data sets. Experiments manifest that the suggested strategy outperforms the existing technique for detecting forest fire smoke.

To investigate image-type fire flare identification, X. Huang et al. employed a support vector machine and semantic similarity theory. In reality, the RS technique is susceptible to noise and has poor automatic failover and generalization performance, whereas the SVM approach has high antinoise and generalization capabilities [7]. This study developed a fire flame photo recognition classifier using an RS-SVM fire flare identification approach. This study employed additional feature variables as the criterion, represented the static and dynamic aspects of flames, selected and extracted the most efficient feature subsets, fused the features of fire flame pictures extracted, and decreased the amount of training necessary to detect and extract flame areas by developing a model with SVM and optimizing the parameters.

H. Yang et al. developed a non-temporal lightweight fire detection approach using CNN. Because a fire object varies from other objects in terms of properties, notably color, the authors recommend using a channel multiplier to boost the color aspects in their network. Because fire is a deformable object, they also use SE-Depthwise modules to enhance the representation of depthwise separable convolution to capture the global features of fire effectively [8]. Furthermore, despite traditional CNNs' strong classification performance, inferences take a long time because of the large number of parameters. They address this issue by reducing network complexity, allowing CNN to be used in embedded devices with limited computing capability.

C. Fan et al. present an inconspicuous wearable system that depends on a wireless body area network that consists of a smartphone and a wristwatch to identify smoking episodes. The system makes full use of the rich motion context of both ubiquitous gadgets and can anticipate smoking occurrences in real-time on the phone. Furthermore, an end-to-end trainable unified learning model that fully utilizes both the VAE and random forest properties is provided. In this model, the VAE is used to learn the latent representations and true distribution of the imbalanced input data. The neural decision forest, a differentiable random forest that uses the representations as input to create the final prediction, is then utilized [9]. The presented system surpassed a variety of comparative approaches in terms of accuracy and efficiency, and it attained state-of-the-art performance, according to thorough testing data.

Y. -J. Kim et al. developed a reliable building fire detection mechanism for fire safety in particular building contexts using simulation-based learning. We initially provided modeling and simulation methods using structural, state, and event representations to produce artificial training data that reflect actual physical buildings. Then, MEDNet was created to identify fire incidents and forecast divergences among real input data and all simulated training data using a model complexity [10]. By applying the data-independent knowledge-based technique in a timely way, the dissimilarity prediction enables the functioning of the switching measure to prevent erroneous predictions, which can arise if unexpected circumstances are encountered.

M. D. Nguyen et al. propose a video-based fire detection algorithm for use in a fire-alarm system that is set up early. This technique analyses fire flames in both the spatial and temporal domains by combining a CNN and an LSTM network. Their system outperformed previous methods by combining the benefits of CNNs and LSTM in computer vision applications. Unlike existing systems that apply fire classifiers to complete pictures, missing minor flames, the proposed method includes a fire candidate extraction stage, allowing the system to identify a variety of fire sizes [11]. Furthermore, because the CNN-LSTM model uses tiny cropped fire pictures as input, the introduced technique can be quick.

For smoke detection, a CNN-17 deep convolutional neural network with dark channel pictures as input was built. The dark channel transformation of photos might accentuate the smoke aspects [12]. Weighted softmax loss and a range of data augmentation approaches were utilized to mitigate the effects of unbalanced data and inadequate training samples. Extensive comparison tests indicate that the presented solution for detecting smoke outperforms existing algorithms. CNN17's smoke detection performance might be improved by using dark channel input, weighted softmax loss, and data augmentation approaches, all of which have lower computational complexity than traditional CNNs.

D. Sheng et al. presented a system that combined SLIC-DBSCAN with convolutional neural networks to develop a novel smoke detection method that incorporates a sophisticated background interference splitter and a robust smoke feature extractor. SLIC- DBSCAN is used to segment and rebuild smoke pictures with complicated backgrounds [13]. The potential pure smoke images are then trained using the convolutional neural network for feature extraction and classification. The results of the experiment suggest that the present approach is capable of identifying smoke images with increased accuracy, making it suitable for use in smoke detection. Combining SLIC with DBSCAN to deal with smoke images with complex backgrounds may be a good option based on past studies. The CNN model is used to identify fire situations because of its excellent capacity in fire and smoke picture feature learning and pattern recognition.

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III. PROPOSED METHODOLOGY

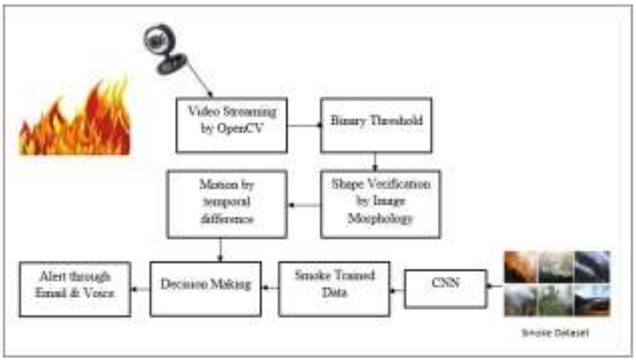

Fig. 1: Proposed model Overview

This part of the research paper mainly concentrates on revealing the details of the proposed model that is incorporated for the deployment of the fire detection model using the multi-classifier model and CNN supervised model. The steps that are undertaken for the deployment system are narrated below in depth.

Step 1: Video streaming - This is the primary step that focuses on streaming of images from the deployed web camera to the developed system. For the ease of development the proposed system installs the java based open CV to integrate the existing camera hardware with the developed project source code. With the extensive help of the opencv video is streamed from the camera into the instance media player. Then a for every set timings a frame is grabbed and stored in the specific location and also into a instace queue.

Step 2: Binary Threshold (Color classifier) - In this step an image frame is being fetched from the queue by an instance thread to evaluate for the fire color. Here in this process every pixel of the image is being traversed to extract the pixel's signed integer value, which is unique for each existed color. This signed integer value is utilized to extract the respective RGB values by right shifting 16, 8 and 0 bits respectively. The obtained RGB value for the respective pixel is subjected to estimate their average values. If the obtained average value is greater than a said threshold value, then the pixel is converted into white color by assigning the values of the RGB to (255,255,255). On the other hand pixel is turned down to black color by assigning the values of the RGB to(0,0,0). This is due to the fact that, bright pixels in the image like fire are always having a value of RGB nearer to 255, else 0. After conversion of pixels into white and non-white in the image, fire pixels looks like white and all other pixels are in black. This process yields a binary image in black and white. The Mentioned technique is denoted in the algorithm 1 below.

ALGORITHM 1: Binary threshold for Fire detection using color component

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// Input: Video Frame **F**
// Output: Fire detected image

Step 0: Start
Step 1: Get Image path.
Step 2: Get Height and width of the Image **F** (L*W).
Step 3: FOR **i**=0 to width.
Step 4: FOR **j**=0 to Height.
Step 5: Get a Pixel at (i, j) as signed integer.
Step 6: Convert pixel integer value to Hexadecimal to get R, G, and B.
Step 7: **AVG**=(R+G+B) /3
Step 8: **IF AVG** >**T** (T is Threshold)
Step 9: Pixel at (i,j) is FIRE
Step 10: **ELSE**
Step 11: Pixel at (i, j) is NOT FIRE
Step 9: End of inner for
Step 10: End of outer for
Step 11: Stop

Step 3: shape verification- The obtained binary image which in turn indicates fire as white pixel and the rest in black pixels are utilized to form a coaxial ratio array to indicate the shape of the fire. In this process every white pixel position with respect to a particular axis is estimated for its ratio to obtain an array for the fire shape of a particular frame. This array of instance frame is compared with the array of the next frame to measure the change of the shape of the fire. If the changes in the shape array or co-axial array is greater than the set threshold, then the instance frame is being considered to have a positive fire. The morphology or co-axial ratio can be represented by the equation 1 and 2. This frame is then being subjected to estimate the fire motion in the next step

$$M(x) = \sum_{i=1}^{N} P\,(i,j,[255,255,255])/WIDTH \quad \text{\_\_\_\_\_(1)}$$

$$M(y) = \sum_{i=1}^{N} P\,(i,j,[255,255,255])/HEIGHT \quad \text{\_\_\_\_\_\_\_\_(2)}$$

Where M(x) – Morphology vector related to X axis.
M(y) – Morphology vector related to Y axis.
P(i,j) – Pixel at position i and j
N – Number of pixels in the image

Step 4: Motion by Temporal Effect- This is the third step of the color classification for the identification of the fire

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through motion. In this process the instance frame is listed for the fire pixel position, this list is being compared with the past list to get the absolute difference. If the difference is more than the set threshold then the frame is labeled as the fire. This process is denoted in the below algorithm 2.

Algorithm 2: Fire Detection by motion

// Input: Time **T**, Frame $\mathbf{F_c}$, Frame $\mathbf{F_p}$, Threshold Fire pixels $\mathbf{T_h}$
// Output: Fire Detection through motion
Step 0: **Start**
Step 1: **WHILE** (TRUE)
Step 2: for each time **T**
Step 3: $F_p \rightarrow F_c$
Step 4: calculate pixel positions of $\mathbf{F_p}$ in an vector $\mathbf{V_p}$
Step 5: calculate Pixel positions of $\mathbf{F_c}$ in an vector $\mathbf{V_c}$
Step 6: IF ABSOLUTE DIFF ($\mathbf{V_p} - V_c$) > $\mathbf{T_h}$
Step 7: Label Frame for Fire
Step 8: **END IF**
Step 9: **END WHILE**
Step 10: Stop

Step 5: Convolution Neural Network (CNN) for Smoke – A data set of images from the URL: https://github.com/DeepQuestAI/Fire-Smoke-Dataset is used for the purpose of the training the dataset using the convolution neural network. This training is done for the three classes like Fire, Neutral and smoke with the below mentioned architecture for the CNN in the table 1.

Layer Parameters	Activation Function
32 x 3 x 3 2D	ReLU
MaxPooling2D (3x3)	
Dropout (0.25)	
64 x 3 x 3 2D	ReLU
64 x 3 x 3 2D	ReLU
MaxPooling2D (3x3)	
Dropout (0.25)	
128 x 3 x 3 2D	ReLU
128 x 3 x 3 2D	ReLU
MaxPooling2D (2x2)	
Dropout (0.25)	
Flatten	
Dense (1024)	ReLU
Dropout (0.50)	
Dense (2)	Sigmoid

Table 1: CNN Architecture

After the completion of the training dataset through the python programming language, the obtained results are stored in the .h5 file, which is further will be used by the decision making model of the next step.

Step 6: Decision making- The obtained results for the instance frame through color, shape and motion classification is labeled with the weight of numerical value. This frame is then tested with the trained data with respect to the stored.h5 model file of CNN for the presence of the smoke. Based on this result a decision is taken to announce the instance image as fire or non-fire along with its intensity as VERY LOW , LOW, MEDIUM, HIGH and VERY HIGH using the IF-then Rules.

This result is then utilized to intimate the premises owner who installed this fire detection system with an email and fire event snap.

III. RESULTS AND DISCUSSIONS

The presented approach has been realized using the Java programming language through the utilization of the NetBeans Integrated Development Environment as the standard IDE. The proposed approach has been evaluated for its effectiveness and for this purpose an extensive evaluation metrics have been realized through the following tests given below.

The evaluation of the system has been performed on the publicly available fire images that are downloaded from the URL:http://mivia.unisa.it/datasets/video-analysis-datasets/fire-detection-dataset/.

Different types of the images are been set to identify the fire by our system as shown below.

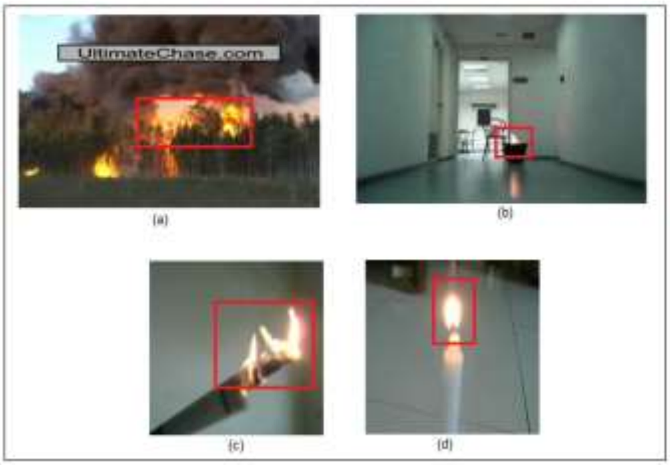

Figure 2: (a) and (b) images shown detection of fire and they are taken from the datasets. (c) And (d) images showing the detection of fire which are collected form the live streaming the videos from our camera.

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As the fire is a subjective and requires the observation by an actual human being to realize the authenticity of the fire. This is useful in understanding the accuracy of the approach in identifying the occurrence of fire. Therefore, the paradigm of MRR or Mean Reciprocal Ratio is being deployed. Through this approach the human perfection can be realized in the presented approach.

Through the use of the MRR approach, the user assigns a rank to the output image based on the perfection achieved. This rank is in the range of 1 to 6, where the rank of 1 signifies highly accurate identification of the fire, whereas the rank of 6 defines the lowest precision achieved by the presented approach. The rank of 1 is depicted as 1, the rank of 2 is being depicted as 1/2, a rank of 3 as 1/3, then ¼ and lastly 0.

Therefore, for a set of images containing fire are subjected for evaluation and the resultant outcomes are provided a rank which is then utilized in the equation 3 and 4 given below.

$$S = \sum_{i=1}^{n} 1 / (Ranki) \text{ \_\_\_\_\_\_\_ } (3)$$

MRR=S/N _______ (4)

Where n – Number of input images

The Mean Reciprocal Ratio is evaluated for 25 images of different kinds and the outcomes for the same are illustrated in the table 2 given below.

S. no	Fire Image Type	MRR
1	Office	0.79
2	Forest	0.9
3	Building	0.76
4	Corridor	0.85
	Mean	0.825

TABLE 2: Recorded MRR

FIGURE 3: MRR COMPARISON FOR DIFFERENT TYPES OF IMAGES

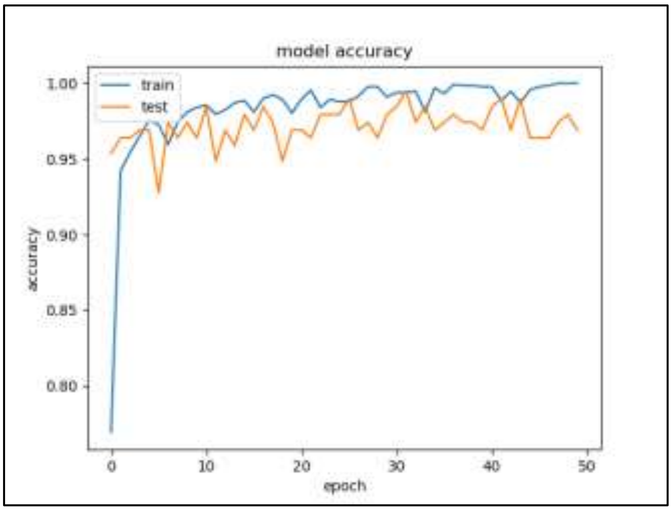
The graph stipulated in the figure 3 above dictates the superiority of fire detection displayed by the proposed methodology. The Average MRR achieved by this technique is 0.82. This is a highly satisfactory outcome that indicates an extremely accurate implementation of the multi-classifier fire detection approach.

Model Accuracy and Model Loss for training and testing of Convolutional Neural Networks

For the purpose of smoke detection the proposed approach deploys the Convolutional Neural Networks that are trained and tested extensively on the dataset achieved from the URL - https://github.com/DeepQuestAI/Fire-Smoke-Dataset. This dataset consists of images of 3 different classes, namely, Fire, Neutral and Smoke. The python programming language has been utilized for this purpose. The training and testing has been performed for 50 epochs for dry testing and the resulting model accuracy and the Model loss achieved are displayed below.

Figure 4: Model Accuracy

The smoke detection supervised system has also been evaluated for its accuracy achieved by the smoke detection approach. The training has been performed for 50 epochs



which has led to the generation of the accuracy vs number of epochs graph as shown in the figure 4 given above. This graph indicates that the accuracy of the model increases sharply in the initial epochs while training and then stabilizes with quite accurate results.

Figure 5: Model Loss

The model loss is also evaluated and the resultant graph for 50 epochs is shown in the figure 5 given above. As evident from the graph given above, the model loss decreases sharply

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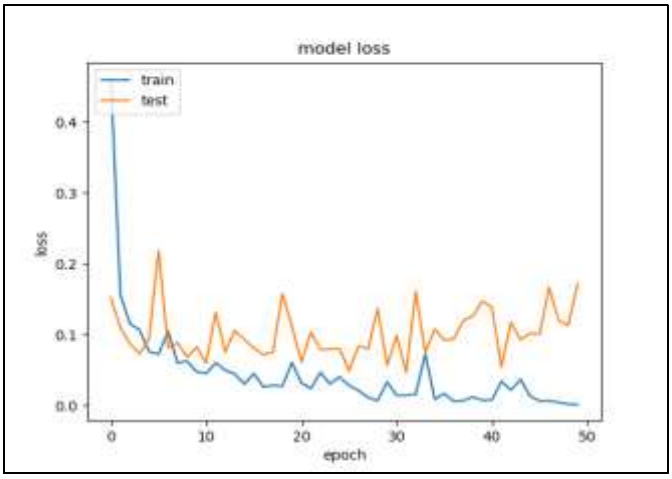

in the initial epochs for the model execution. This results in a sustained lower loss over 50 epochs which indicates an exceptional training and testing performance which translates quite well to the real world performance for the multi-classifier fire and smoke detection.

V CONCLUSION

The presented approach for fire and smoke detection has been defined in detail in this research article. There have been increased incidences of fires that have been extremely deadly which have led to the increased loss of life, biodiversity and also billions of dollars' worth of property. This is undesirable phenomenon which can be quite difficult to mitigate before it's too late. Therefore, for this purpose an effective and timely detection of fire is paramount to reducing these occurrences considerably. For this purpose an effective multi-classifier approach has been defined in this research article which identifies the fire as well as the smoke to achieve timely detection of the fire. The approach utilizes a video stream to achieve the frames in which the fire needs to be detected. These frames are utilized for color detection through binary threshold, after which the temporal difference is evaluated for the identification of the motion of the fire and finally the shape of the fire is verified using morphology. This multi-classifier approach is augmented by the smoke detection approach that is achieved through the implementation of Convolutional Neural Networks. The extensive evaluation techniques have been crucial in displaying the superiority of the proposed approach.

The future direction for research can be to deploy this approach in cameras of lower resolution in areas such as thick rainforests and other critical areas for detection of the wildfire.

REFERENCES

1. *K. Muhammad, J. Ahmad, I. Mehmood, S. Rho, and S. W. Baik, "Convolutional Neural Networks Based Fire Detection in Surveillance Videos," in IEEE Access, vol. 6, pp. 18174-18183, 2018, DOI: 10.1109/ACCESS.2018.2812835.*
2. *J. Widodo, Y. Izumi, A. Takahashi, H. Kausarian, D. Perissin, and J. T. Sri Sumantyo, "Detection of Peat Fire Risk Area Based on Impedance Model and DInSAR Approaches Using ALOS-2 PALSAR-2 Data," in IEEE Access, vol. 7, pp. 22395-22407, 2019, DOI: 10.1109/ACCESS.2019.2899080.*
3. *G. Xu, Q. Zhang, D. Liu, G. Lin, J. Wang, and Y. Zhang, "Adversarial Adaptation From Synthesis to Reality in Fast Detector for Smoke Detection," in IEEE Access, vol. 7, pp. 29471-29483, 2019, DOI: 10.1109/ACCESS.2019.2902606.*
4. *S. Luo, X. Zhang, M. Wang, J. -H. Xu and X. Zhang, "A Slight Smoke Perceptual Network," in IEEE Access, vol. 7, pp. 42889-42896, 2019, DOI: 10.1109/ACCESS.2019.2906695.*
5. *Z. Lin et al., "A Contextual and Multitemporal Active-Fire Detection Algorithm Based on FengYun-2G S-VISSR Data," in IEEE Transactions on Geoscience and Remote Sensing, vol. 57, no. 11, pp. 8840-8852, Nov. 2019, DOI: 10.1109/TGRS.2019.2923248.*
6. *Y. Cao, F. Yang, Q. Tang, and X. Lu, "An Attention Enhanced Bidirectional LSTM for Early Forest Fire Smoke Recognition," in IEEE Access, vol. 7, pp. 154732-154742, 2019, DOI: 10.1109/ACCESS.2019.2946712.*
7. *X. Huang and L. Du, "Fire Detection and Recognition Optimization Based on Virtual Reality Video Image," in IEEE Access, vol. 8, pp. 77951-77961, 2020, DOI: 10.1109/ACCESS.2020.2990224.*
8. *H. Yang, H. Jang, T. Kim, and B. Lee, "Non-Temporal Lightweight Fire Detection Network for Intelligent Surveillance Systems," in IEEE Access, vol. 7, pp. 169257-169266, 2019, DOI: 10.1109/ACCESS.2019.2953558.*
9. *C. Fan and F. Gao, "A New Approach for Smoking Event Detection Using a Variational Autoencoder and Neural Decision Forest," in IEEE Access, vol. 8, pp. 120835-120849, 2020, DOI: 10.1109/ACCESS.2020.3006163.*
10. *Y. -J. Kim, H. Kim, S. Lee and W. -T. Kim, "Trustworthy Building Fire Detection Framework With Simulation-Based Learning," in IEEE Access, vol. 9, pp. 55777-55789, 2021, DOI: 10.1109/ACCESS.2021.3071552.*
11. *M. D. Nguyen, H. N. Vu, D. C. Pham, B. Choi, and S. Ro, "Multistage Real-Time Fire Detection Using Convolutional Neural Networks and Long Short-Term Memory Networks," in IEEE Access, vol. 9, pp. 146667-146679, 2021, DOI: 10.1109/ACCESS.2021.3122346.*
12. *X. Shi, N. Lu and Z. Cui, "Smoke Detection Based on Dark Channel and Convolutional Neural Networks," 2019 5th International Conference on Big Data and Information Analytics (BigDIA), 2019, pp. 23-28, DOI: 10.1109/BigDIA.2019.8802668.*
13. *D. Sheng, J. Deng, and J. Xiang, "Automatic Smoke Detection Based on SLIC-DBSCAN Enhanced Convolutional Neural Network," in IEEE Access, vol. 9, pp. 63933-63942, 2021, DOI: 10.1109/ACCESS.2021.3075731.*