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Onspot Fire Detection and Recovery Using Dark Neural Network

Aakash D[1], Anbarasan R[1], Jones Paul R[1], Naresh B[1], P.Venkateswara Rao[2]

UG Student, Dept. of I.T., Panimalar Engineering College, Chennai, Tamilnadu, India[1]

Assistant Professor, Dept. of I.T., Panimalar Engineering College, Chennai, Tamilnadu, India[2]

ABSTRACT: An accidental fire is a mishap that could be either man-made or natural. Accidental fire occurs frequently and can be controlled but may at times result in severe loss of life and property. Fire detection using hand-crafted features is a tedious task. The accuracy of the existing system using Alex net is 77% to 92%. The Project main idea is to detect the fire as soon as possible .The main concept used in the project is Face net pertained model. It is recognition technique to detect the fire on the Surroundings. The embedded processing capabilities of smart cameras have given rise to intelligent CCTV surveillance systems. Fire is the most dangerous abnormal event, as failing to control it at an early stage can result in huge disasters, leading to human, ecological and economic losses. Inspired by the great potential of CNNs, propose a lightweight CNN based on the Squeeze Net architecture for fire detection in CCTV surveillance networks. A Project approach can both localize fire and identify the object under surveillance. The accuracy of the system using Face net is 97%.

KEYWORDS: Data Mining; Voice Recognition; Speech to Text Conversion; Database Connectivity; Speech synthesis;

I. INTRODUCTION

With the rapid spread of urbanization in the world, both the number of permanent residents in cities and the population density are increasing. When a fire occurs, it seriously threatens people's lives and causes major economic losses. According to incomplete statistics, there were 312,000 fires in the country in 2019, with 1,572 people killed and 1,065 injured, and a direct property loss of 3.72 billion dollars. Fire detection is vitally important to protecting people's lives and property. The current detection methods in cities rely on various sensors for detection including smoke alarms, temperature alarms, and infrared ray alarms. Although these alarms can play a role, they have major flaws. First, a certain concentration of particles in the air must be reached to trigger an alarm. When an alarm is triggered, a fire may already be too strong to control, defeating the purpose of early warning. Second, most of the alarms can only be functional in a closed environment, which is ineffective for a wide space, such as outdoors or public spaces. Third, there may be false alarms. When the non-fire particle concentration reaches the alarm concentration, it will automatically sound the alarm. Human beings cannot intervene and get the latest information in time. To prevent fires and hinder their rapid growth, it is necessary to establish a monitoring system that can detect early fires. Establishing a camera-based automatic fire monitoring algorithm and facenet model. Greatly reducing the cost increases the economic feasibility of such systems. In the preprocessing module, the frame difference detection operates quickly and does not include complex calculations, has low environmental requirements, and does not need to consider the time of day, weather, and other factors. The camera-based fire monitoring system can monitor the specified area in real time through video processing

II. RELATED WORK

The Fire detection covers a very large field, and it would be impossible to cover all aspects in one project. The focus in this project is detection using a low-cost camera. This would mean that the program does not only work with expensive technology such as infrared cameras or other such cameras. The cameras that are required to atleast work with this program are the CCTV cameras, such as those in shopping complexes or malls. One factor that needs to be taken into consideration is that, unlike other fire detectors, this system is not a point type detector. It should be able to detect fire in large open spaces, so that the whole scenario must be considered, and not just a single point on the image from the video feed. A system that can also be used in aggressive environments as well as in hazardous areas.

III. PROPOSED ALGORITHM

Our Project idea is to detect the fire and avoid the damages and loses in human life and properties. Fire can be detected using video surveillance in deep learning using Convolution Neural Network (CNN) Algorithm. This Algorithm has four-layer Convolution layer, max pooling layer and ReLU. Convolution layer takes input as matrix representation and then features of the image are extracted within this layer using filter. The output of the convolution layer is passed into Rectified Linear Unit (ReLU) Layer. The ReLU Layer extract positive values portion from matrix based on activation function. The output is passed through the Max pooling function to obtained maximum value for each patch of the feature map. Now Using fully connected layer the output is compared with the fire dataset and the result is produced.

ADVANTAGE:

- Fire can be detected at the initial stage
- To avoid the loss of human life and a wealth
- The accuracy of the system using Facenet is 98%.

IV. PSEUDO CODE

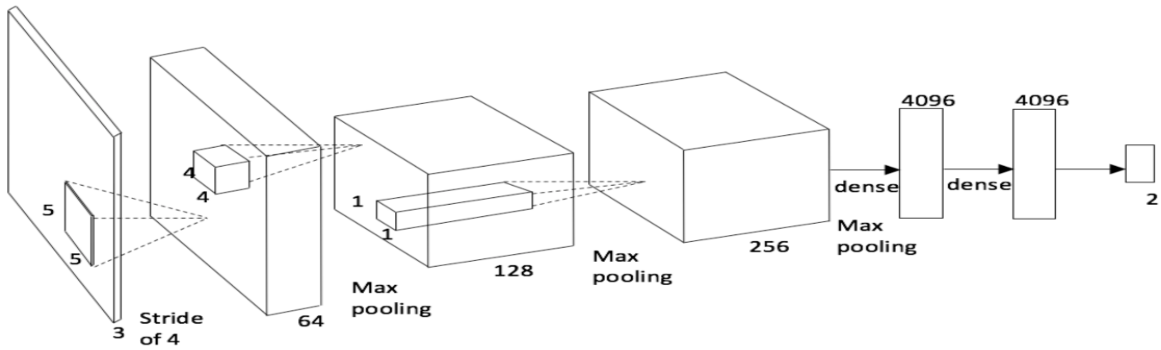
Step 1: User has to generate voice through microphone.
Step 2: Recognised voice should be noise eliminated using HMM
Step 3: Below Formula given the HMM model to convert speech into text

$$\mathrm{P}(\mathrm{q}1,\ldots,\mathrm{qn}|\mathrm{x}1,\ldots,\mathrm{xn}) = \frac{\mathrm{P}(\mathrm{x}1,\ldots,\mathrm{xn}|\mathrm{q}1,\ldots,\mathrm{qn})\mathrm{P}(\mathrm{q}1,\ldots,\mathrm{qn}}{\mathrm{P}(\mathrm{x}1,\ldots,\mathrm{xn})}$$

$$\mathrm{P}(\mathrm{q}1, \ldots, \mathrm{qn}) = \prod\nolimits^{n}_{i=1} \mathrm{P}(\mathrm{qi}\ |\mathrm{qi}-1).$$

Step 4: Given formula convert the speech into text.
Step 5: It connects with the server database using Google search engine.
Step 6: Displaying the relevant links on browser
Step 7: Again it coverts speech into text and go to step 2.
Step 8: End.

V. SYSTEM ARCHITECTURE



VI. CONCLUSION AND FUTURE WORK

This project show that reduced complexity CNN, experimentally defined from leading architectures in the field, can achieve 0.93 accuracy for the binary classification task of fire detection. This significantly outperforms prior work in the field on non-temporal fire detection at lower complexity than prior CNN based fire detection. Furthermore, reduced complexity FireNet and InceptionV1-OnFire architectures offer classification accuracy within less than 1% of their more complex parent architectures at 3-4_ of the speed (FireNet offering 17 fps).

To these ends, project illustrate more generally a architectural reduction strategy for the experimentally driven complexity reduction of leading multi-class CNN architectures towards efficient, yet robust performance on simpler binary classification problems.

VII. FUTURE ENHANCEMENT

This Project mainly focuses on the detection of fire and its localization, with comparatively little emphasis on understanding the objects and scenes under observation. Future studies may focus on making challenging and specific scene understanding datasets for fire detection methods and detailed experiments. Furthermore, reasoning theories and information hiding algorithms can be combined with fire detection systems to intelligently observe and authenticate the video stream and initiate appropriate action, in an autonomous way.

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