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Edge Computing in Micro Data Centers for Firefighting in Residential Areas of Future Smart Cities

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Abstract*—5G standardization is going to reach its end, so research on 6G has started, driven by the scientific and industrial communities. 5G and especially 6G, are going to provide resources to enhance every aspect of human life via communication networks and computing. Among the different verticals, emergency services are one of the most important parts of making smart cities of the future a reality. In this context, firefighting is highly important for security and safety. However, firefighting requires ultra-reliable and low-latency communications since firefighters can be provided with advanced guidance during fire control with the employment of distributed sensors, robots, etc. Also, the use of machine learning algorithms is important for firefighters to analyze and make decisions based on the audiovisual and possibly tactile information they collect. Such a scenario cannot leverage the current cloud computing paradigm, which has significant latency issues. That is why it is important to study and design edge computing paradigms to address the goals of these scenarios and use cases since they can be capable of fulfilling latency and reliability requirements. In this situation, this work looks into how computing at Edge Micro Data Centers (EMDC) can be used to improve how fires are predicted and managed. We propose a novel three-stage architecture. The initial stage focuses on prediction and classification of the fire occurrence based on available sensor data at the EMDC, whereas the second stage deals with the fire occurrence confirmation using a convolutional neural network (CNN) classification model. After the fire occurrence has been confirmed, the final stage notifies the tenants and streams 360-degree monitoring video to the nearby fire station after processing at EMDC. The results showed that the proposed architecture can realize firefighting services with low latency. To the best of the authors' knowledge, this is the first work studying and experimentally evaluating this communication scenario by also involving prediction via intelligence.

***Index Terms*—Smart cities, 5G, 6G, Edge micro data centers, Convolutional neural networks.**

I. Introduction

In 2015, the General Assembly of the United Nations have provided seventeen interlinked Sustainable Development Goals, identified to shape "a better and more sustainable future for all" [1]. Since then, all sectors of society have been involved for achieving these goals by 2030. Among the various industries, Information and Communication Technologies (ICT), and so wireless networks, have been identified as a key industry to contribute to all the seventeen goals. In this sense, current 5G and especially future 6G technologies have been researching and designing their architectures towards these goals. Among the seventeen goals the improvement of quality of life in cities is pivotal. In fact, smart cities have been representing a fundamental use case for the Internet of Things in 5G and now in 6G. In this context, emergency services play a vital role for human welfare. One fundamental emergency service is firefighting in residential areas. Fire accidents in the residential buildings are increasing day-by-day as per National Center for Biotechnology Information (NCBI) report [2]. Specifically, reports by National Crime Records Bureau (NCRB) [3], revealed an important fact that most of these deaths were caused by home fires — under the category of residential building fire accidents, which are a time-sensitive and mission-critical application.

Most of the residential buildings use traditional firefighting systems, consisting of three main components: (i) fire storage tanks; (ii) dedicated pumping system; and (iii) a system of pipes ending in hydrants (or sprinklers). Fire alarm includes fire sensors such as carbon monoxide detectors, heat and smoke detectors, multi-sensor detectors (combines various detectors input and processing them), and manual call point (triggers alarm). However, the main disadvantage with the above specified setup is that manual intervention is required. Thus, it may trigger false alarm due to the lack of intelligence about the environment. The work in [4] presented how to measure fire risk and level of damage that may be predicted in the event of a fire. Moreover, [5] proposed a model to analyze the fire risk based on scenario clusters to take an appropriate fire risk management measures in buildings.

With the advent of 5G and cloud/edge computing, Machine Learning (ML) algorithms have started being provided to enhance and enable use cases and services. Authors in [6] investigated the impact of ML technology, 5G and beyond network on the emergency health care services (fire brigade, ambulance services, etc,). However, it specifically focused on providing emergency services using intelligent vehicles but not related to the fire circumstance. In [7], an IoT-based architecture was presented, which requires a prior information about the building such as number of floors, firewater system and real-time occupant data, and many other. The work mainly focused on notifying to all the occupants based on alarms and launching fire control equipment using IoT.

A cloud based firefighter safety-centric approach was described in [8]. It is critical to know the fire and firefighters position using radio technology which requires large scale sensor reading analysis. Due to the huge volume of sensor data being transmitted over the Internet, the cloud-based solution has one significant drawback: it has a longer system's response time.

An edge based approach was presented in [9] to address the firefighter safety by setting an edge server near the fire accident and access video, audio, and various gases information to understand the fire circumstance as well to guide them in order to rescue the occupants. Even though it is an effective edge based approach, it is mainly focused on firefighters safety; however, the fighters will not have details on intelligence in preventing the fire or forecasting the fire.

More precisely, some of the disadvantages with the existing approaches are as follows: (i) Inadequate data centers near to the buildings to process real-time data; (ii) Lack of information about the fire circumstance; (iii) the means of communication between the fire station and available devices in the residential area; and (iv) Communicating the processed data within the minimum round-trip latency.

To the best of authors' knowledge, no prior work has addressed the above issues. This paper proposes a novel architecture to alleviate these issues by exploiting Edge Micro Data Centers (EMDCs) [10]. Edge computing is an in-network computing paradigm that started with 5G, consisting of moving data processing, and also computing due to intelligence, closer to the end users, for being able to serve both time-sensitive and mission-critical applications effectively. EMDCs are small, cost-effective data centres that have all the nodes needed to complete a task, such as storage, compute, networking, and other hardware and tools. Edge accelerated micro data centers provide faster processing and storage near data sources.

This paper proposes a three stage novel architecture for residential building fires. Initially, data collected from various sensors are gathered at the edge. Then, the system predicts and classifies the occurrence of fire using ML models (e.g., LSTM model and Random forest) in *Stage-I* and then proceeds to Stage-II if fire is suspected. *Stage-II* enables a camera, which is in the residential area and feed images/frames to a pre-trained Convolutional Neural Network (CNN) model for image classification, in order to get a confirmation about the fire accident. Finally, the fire monitoring station can get information (e.g., tactile feedback) of fire circumstance through interaction with a 360-degree video camera or drone as a part of *Stage-III*.

II. System Model and Proposed Scheme

The above stated shortcomings are addressed by our proposed architecture as following: (i) maintaining data centers close to residential buildings is an expensive task but it can be mitigated by employing EMDC — more details about EMDC is described in the following section; (ii) streaming a 360° video from fire accident area, fire monitoring station can easily understand the fire circumstance and directs the firefighters accordingly — Stage-III module plays a major role to achieve this; (iii) the fire monitoring station may interact with the fire environment by controlling the camera or drone and recognise the seriousness of the situation and prevent it from occurring; (iv) EMDC meets the low-latency due to high speed pre-processing, effective computation, and other hardware components.

Figure II presents the proposed three-stage architecture for fire accidents in residential buildings. It has three important stages: (i) *Stage-I* predicting the occurrence of the fire from wireless sensor data; (ii) *Stage-II* enables cameras (which is located in residential building) and feeds the captured images to a pre-trained CNN image classification model if the occurrence of fire is true; and (iii) *Stage-III* streams the 360-degree video monitoring to the nearby fire station and sends an automatic notification upon fire accident occurrence confirmed. The following subsections describes the proposed stages.

A. Data fusion and Pre-processing

For real-time monitoring and sensing of fire-related characteristics in residential areas, wireless sensor networks (WSN) plays a crucial role. Data is often repetitive in WSNs. It is impossible to provide more information to the user by communicating raw data than it is by delivering aggregated data. In addition, transferring raw data may lead to data collisions, which will increase the network's cost and decrease the effectiveness of information gathering. The user will receive erroneous results if these data are sent without processing. All the information sensed in a given region may be processed via data fusion using the edge micro data center (EMDC).

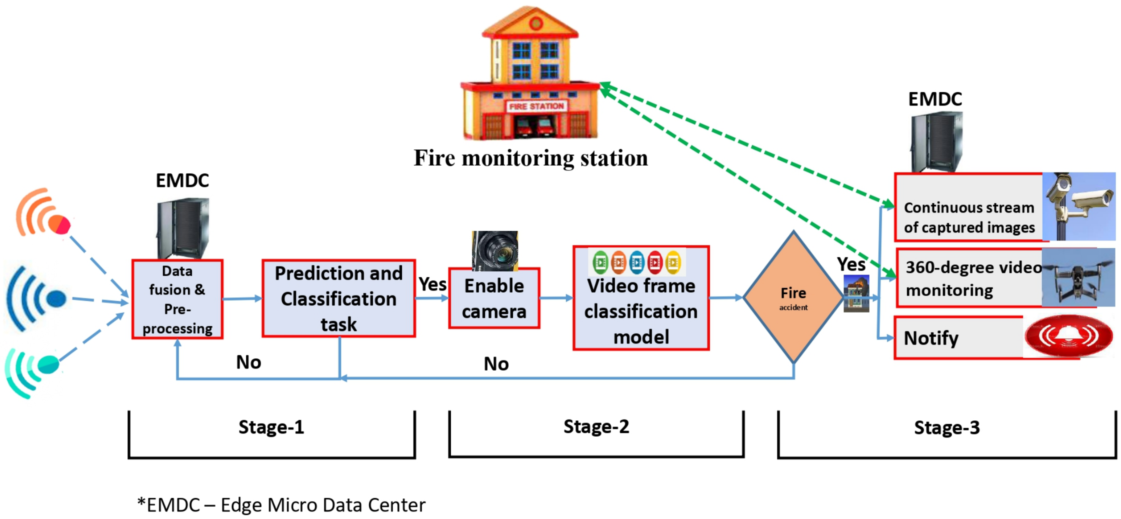

Fig. 1. Proposed end-to-end architecture

EMDC is a small-scale data center deployed by edge-cloud and telecommunications operators in close proximity to WSN. *EMDCs* are the light weight versions or the smaller version of a traditional data centers. Since these are tiny versions, it is cost effective. *EMDCs* usually consists of cluster of nodes. Data is collected using set of sensors i.e., from edge devices. This sensor generated data is sent to the EMDCs called edge nodes. At *EMDC*, data fusion takes place and after that pre-processing technique is applied on the fused data to make it ready for the further processing. Due to the acceleration of *EMDC*, the response time is very less — fire based applications requires strictly low response time. Hence *EMDC* is adaptable for the low-latency requirement. Moreover, the data is sent to the EDMC for fusion, the bandwidth consumption will be reduced.

B. Stage-I: Prediction and classification task

Each feature of processed data fed to a time series AI/ML model for training purpose, so that it will generate inference module to predict corresponding feature values (e.g., Oxygen, Temperature, and Humidity) in near future and random forest classifier enabled over those predicted features to determine whether fire has occurred or not. If the classification results in fire occurrence, it proceeds to the *Stage-II* otherwise remains at the *Stage-I*. Figure 2 shows the overall prediction and classification mechanism.

C. Stage-II: Enabling camera and frame classification

Suspecting occurrence of fire leads us to *Stage-II* which gives us confirmation about the fire accident. The main contribution of this stage is to avoid false alarms, which is a major disadvantage in the most of the existed systems. Once predicted feature set meet the fire occurrence, it directly enables the camera(s) at the residential area and feed all the captured images to a CNN fire image classification model in order to get the confirmation about the fire accident. At this stage, we double check about the fire accident and proceed to *Stage-III* if fire accident occurs otherwise switch to *Stage-I*.

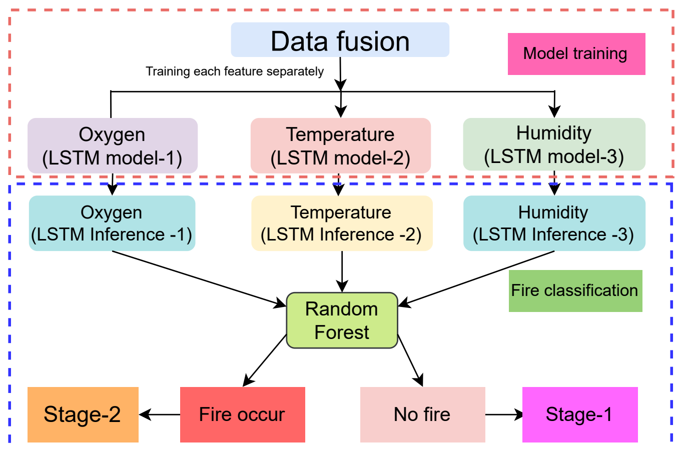

Fig. 2. Fire prediction and classification mechanism at Stage-1

D. Stage-III: 360° video streaming with low latency

Once the CNN fire image classification model detects the fire in residential building area as a part of *Stage-II*, it proceeds to the *Stage-III*. Final stage enables a 360° video streaming to the fire station by collecting all the images and perform data fusion at the EMDC to produce a 360° video otherwise launches a drone which is available at the building. All the camera(s) and drone(s) controlled by the fire station and establishes a dedicated communication link with a low communication latency.

The streamed 360° video, often known as panoramic, spherical, or unidirectional video, is a new immersive multimedia format. It's more immersive than a two-dimensional picture. A two-dimensional image can only be viewed in one direction, but a 360° video (or image) may be watched in all directions. Most modern cameras generate equi-rectangular 360° panoramic videos. Fire monitoring station can get an information about various hazards like falling ceiling, collapsing wall, or even chemical gas emission, with which this can aid in routing fire teams. Moreover, the images or videos from the surveillance cameras are sources for discovering how many occupants are trapped and even where they may be.

III. Experimental setup and results

Experimental setup for all three stages explained in detail in the following sections.

A. Experimental setup

1) Data-set: To implement the proposed methodology, we created a data-set consists of 220 entries which has three main features of fire (Oxygen, Temperature, and Humidity). An increase in both oxygen and temperature as well decrease in humidity causes fire. Same way, a decrease in oxygen and temperature but increase in humidity avoids fire occurrence according to [11]. [11] has provided a WSN data-set which contains 40 entries and after performing some analysis, we implemented a 220 entries data by keeping it as a reference.

2) Stage-I: Time-series model: The Long short-term memory (LSTM) architecture is a kind of recurrent neural network (RNN) that remembers (or stores / holds) values over arbitrary time periods. The LSTM algorithm is well-suited for forecasting time series when temporal delays of undetermined duration are present and more insights are presented in [12]. We choose uni-variate LSTM for each feature of the fire dataset and feed the predicted feature values to a random forest classifier to determine fire occurrence. Random forest is widely used for classification and regression. It builds decision trees on various samples of the data then considers the major vote for classification [13]. We build three uni-variate models for the corresponding three features and random forest classifier performs fire occurrence classification based on the results at the respective inference modules.

3) Stage-II: Video frame classification model: Whenever the fire is predicted in the time series model, the camera is enabled and the captured images fed to the pre-trained CNN fire image classification model which is shown in Figure 3. Initially, video is sensed from the environment and then converted into a sequence of frames which is then given as input to the CNN model. Proposed CNN model is a simple Sequential architecture that has been built from scratch using 3 Convolutional layers. Then the output of CNN is flattened and then finally, classified using a soft-max layer. Throughout this model, *relu* is used as an activation function except for the last layer. And the model is compiled using binary cross entropy loss function and adam optimizer. Accuracy has been used as the performance metric. Various operations involved in the proposed CNN architecture are discussed below.

Convolution layer: A convolution operation can be equivalent to flip the filter or kernel in both directions (bottom to top and right to left) and apply cross-correlation as represented in Equation 1.

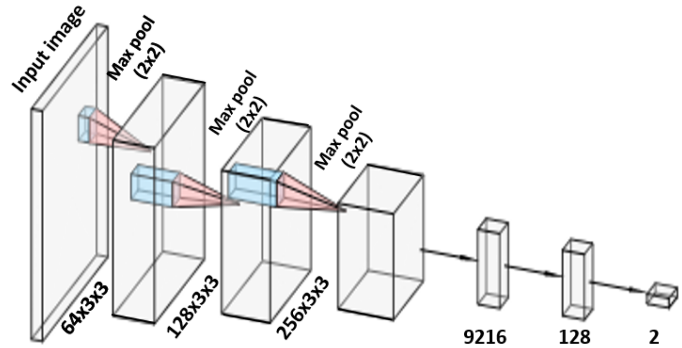

Fig. 3. Proposed CNN architecture

$$G(i,j) = \sum_{u=-k}^{k} \sum_{v=-k}^{k} H(u,v) I(i-u, j-v) \tag{1}$$

where, $H(u,v)$ is the filter or kernel and $I(i,j)$ is the actual image.

ReLU (Rectified Linear Units): It is a very popular activation function which activates a neuron (artificial neuron) based on threshold. ReLU layer output is always positive and represented in Equation 2.

$$f(x) = max(0,x) \tag{2}$$

Pooling: This layer reduces the size of output of a previous layer which reduces number of computations in later layers.

Adam optimizer: Used to update the weights of an artificial neural network in the training phase. There are other optimizers like Gradient Descent, RMSprop, Adadelta, and Adagrad. But, Adam is the popular one because it converges faster compared to other optimizers.

Binary Cross-entropy: Binary cross entropy is a loss function that is often used for binary classification. Whenever we have the probabilities as outputs, binary cross entropy is used and mathematical representation is in Equation 3.

$$Loss = -(y_i \log(p_i) + (1-y_i)\log(1-p_i)) \tag{3}$$

where y_i is the actual output and p_i is the predicted probability.

To develop this stage, we gathered 450 residential building fire accident images from different sources and labelled using LabelImg tool [14]. Trained the proposed CNN architecture with 80% of collected images and the performance is shown in the results section.

4) Stage-III: 360° video monitoring: Whenever fire occurrence confirmed at Stage-II, 360° video monitoring enabled and streamed to fire monitoring station. Firefighters controls the camera or drone in order to understand the fire circumstances. Streaming data highlights fire in the video which can give an information about the flame width/height, smoke propagation, etc.

To implement this stage, we collected a few residential area fire accident videos from different sources and annotated using a LabelImg tool [14]. Among the all available models, YOLO is widely adapted for real-time object detection that has the capability to identify objects in videos, live feeds and images. It is popular due to its speed and accuracy. Hence YOLO [15] is adapted in Stage-III.

B. Results

The LSTM model performed prediction over oxygen, temperature and humidity values and the obtained results is shown in Figure 4. The prediction accuracy, expressed by the root mean square error (RMSE) in Equation 4, is the performance parameter under consideration, and the optimal hyper-parameters are found for each approach.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - \hat{X}_i)^2} \tag{4}$$

where, X_i is the actual output and $\hat{X}_i$ is the predicted output from respective model.

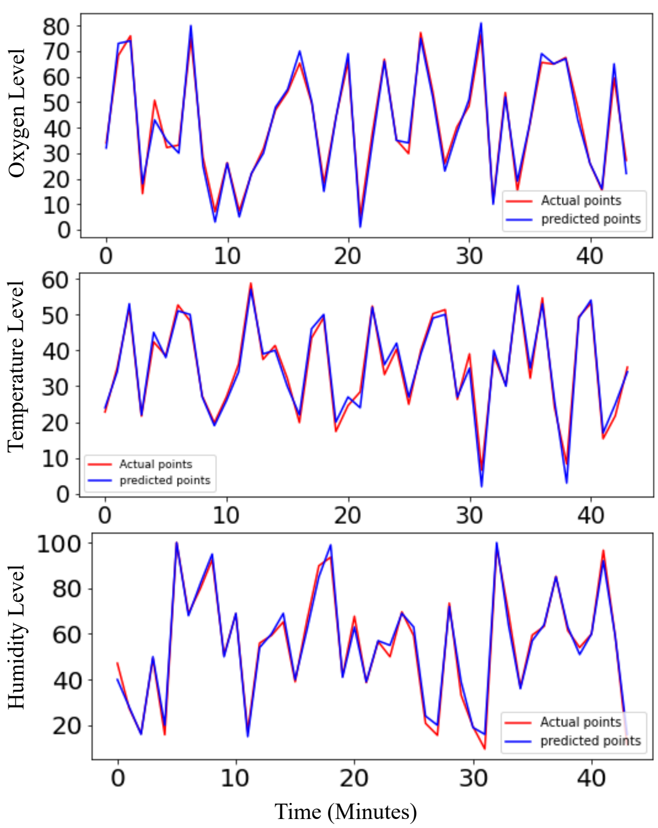

Fig. 4. Uni-variate LSTM Prediction of oxygen, temperature, and humidity

Random forest classifier over the uni-variate LSTMs obtained a good results and is presented in Table I. The CNN fire classification model performance in Stage-II achieved an accuracy of 96% and the training as well validation accuracy is shown in Figure 5. The Stage-III is implemented by adapting the YOLO to the collected residential area fire image dataset. We used base version of the YOLO to implement and 360° video has been streamed to fire monitoring station by highlighting the fire (fire detected regions(s)) in the video and the sequence of few frames in a 360° video stream is shown in Figure 6.

YOLO model performance has been measured using mean average precision (mAP) with 0.5, 0.75 threshold values (α), averageIOU, Precision (P), and Recall (R). The performance metric mAP is determined by taking the mean average precision across all classes and/or the overall IoU thresholds, depending on the detected objects that exist. mAP for a given threshold value α is given in Equation 5.

$$mAP@i = \frac{1}{N}\sum_{i=1}^{N} AP@i \tag{5}$$

Where N corresponds to number of classes and APi is the average precision (AP). AP can be defined as area under the precision-recall curve (AUC-PR) and mathematically represented in Equation 6.

$$AP@i = \frac{1}{n}\sum_{R_i} P(R_i) \tag{6}$$

Where n corresponds to number of interpolation points.
The proposed models' performance metrics at different stages is shown in the Table I.

All of the modules in the proposed architecture were run on a machine with 32GB RAM and 16 cores of CPU. The time taken for prediction of a single instance in Stage-I and for a single frame classification in both the Stages II and III is shown in the Figure 7. The end-to-end time delay can be enhanced using GPU.

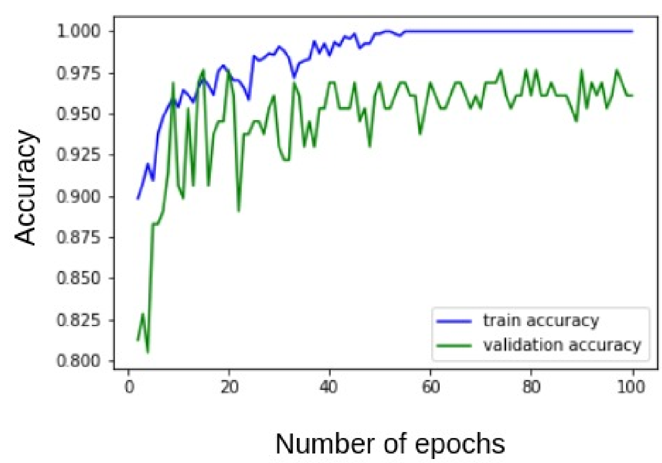

Fig. 5. Video frame classification model performance at Stage-II

IV. CONCLUSIONS

This paper aims at developing a novel approach to address fire accidents in residential areas of future smart cities based on computing at Edge Micro Data Centres (EMDC). The

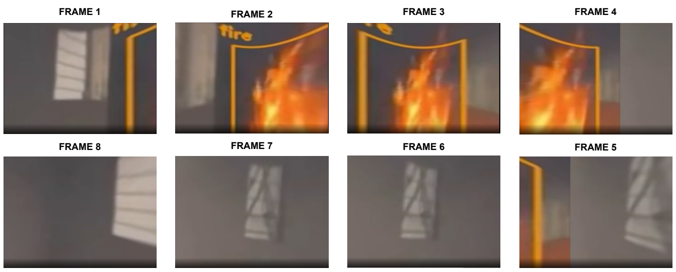

Fig. 6. 360° video stream with fire detection at Stage-III

TABLE I
PROPOSED ARCHITECTURE RESULTS AT DIFFERENT STAGES

Module	Model name	Metric Used	Result
Stage-I	LSMT model-1 LSMT model-2 LSMT model-3	RMSE RMSE RMSE	2.8(Oxygen) 3.2(Temperature) 5.3(Humidity)
Stage-I	Classification	Accuracy Precision Recall F1-score	92.2% 93 91 92
Stage-II	CNN model	Accuracy	96%
Stage-III	YOLO	mAP@50 mAP@75 AverageIOU Precision Recall	76.83% 66.82% 73.23% 0.81 0.73

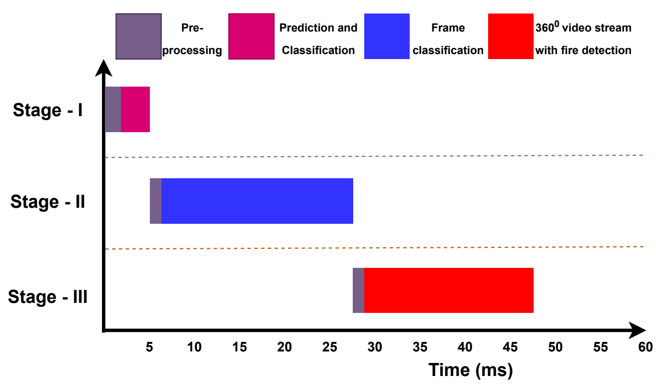

Fig. 7. End-to-end delay of the proposed architecture

sensor data collected from WSN in the Stage-I is used for data fusion and pre-processing at the EMDC. The processed data is further used to predict the occurrence of fire. The possibility of false alarm's is avoided by employing the video frame classification model, which gives us the right confirmation of the fire accident. On getting the positive confirmation about the accident, a 360° video stream of the fire environment is sent to the near by fire-station and an automatic notification is made to alert the people. Results showed that the proposed architecture can provide reliable and low-latency services for fire fighting in residential areas of future smart cities.

Based on this study, this work could go in the following directions in the future: (i) Building the proposed end-to-end architecture in a real-time scenario in order to get more insights about the fire circumstance; (ii) Understanding the fire intensity based on smoke density; and (iii) Predicting the direction of fire at the Stage-III so that firefighters can get a clear idea and prepare accordingly.

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