A Cloud-Based Image Processing Platform for Smart Cities in Iraq

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***Abstract*— Before the concept of a smart city emerged, monitoring and managing cities was done in traditional way. Since the infrastructure of technology gradually became available to smarten up various aspects of urban management, monitoring, and control, the concept of a smart city also emerged. In a smart city, Internet of Things equipments, fast communication networks, sensor networks, surveillance cameras, and so other smart equipments are used to collect data. These data are processed and transformed into meaningful information and ultimately used in city control and management. In a smart city, technology is used to the fullest extent possible to provide better and more efficient services to citizens. Image processing is one of the technologies used in smart cities for various purposes. In this article, we present the architecture of a cloud-based image processing system that uses the MapReduce model. This platform is designed to be implemented in smart cities of Iraq. However, it can be used in other smart cities that have similar architecture. The high volume of data produced by sensors and cameras in a smart city makes it necessary for cloud-based processing systems to prevent processing power issues.**

Keywords*— *MapReduce, image processing, Internet of Things, Ubiquitous Computing, Cloud Computing, Smart City

I. INTRODUCTION

Smart city is defined by IBM as the use of information and communication technology to sense, analyze, and integrate important information of core systems for running cities [1]. At the same time, smart city can make intelligent response to different kinds of needs, including daily livelihood, environmental protection, public safety and city services, industrial and commercial activities [2]. Cities are converting to smart cities one after another and this is happening very fast. Various definitions can be considered for a smart city. The wide adoption of pervasive and mobile computing systems gave rise to the term of "smart cities," which implies the ability of sustainable city growth by leading to major improvements in city management and life in the above-mentioned sectors and other aspects such as energy efficiency, traffic congestion, pollution reduction, parking space, and recreation [3]. Cities are increasing their focus on becoming smart cities by using data management networks such as the Internet of Things (IoT), big data, and cloud computing technologies. These data management systems provide improvements in various aspects of operations and organizations, such as traffic control, sustainable resource management, quality of life, and smart city infrastructure [4, 5]. The rapid development in Internet of Things (IoT) technologies encourages researchers and scientists to create new IoT applications and services, and these new intelligent services should significantly meet the needs of citizens worldwide [6]. In smart cities, equipment such as sensors, sensor networks, cameras, processors, and any type of Internet of Things equipment that can help provide services, surveillance, and city management is used.

In this article, we provide a public platform for cloud-based image processing for smart cities in Iraq that uses the MapReduce processing model. To offer this platform, we need to envision it within the architecture of a smart city to better understand its communication and performance with smart city components. This research can be used in other smart cities that have similar architecture.

II. RELATED WORKS

Several studies have been conducted on smart cities and the use of image and video processing for detecting specific incidents. In this section, we review these studies. The use of sensors and various equipment in a smart city helps to collect a wide range of information. Each sensor can collect a specific type of information. For example, a thermometer records the ambient temperature. A smoke sensor determines the concentration of smoke in the environment, and a pollutant detection sensor determines the level of air or water pollution. Cameras record images, and a device may record the number of people or vehicles passing through a location. The variety of equipment with similar functions is very high, recording and capturing data in different sections. These data may not be important in themselves. But when processed, they become meaningful and turn into valuable information that can be used in the control and management of a smart city. The data produced at any moment have a very large volume and are known as big data. In the past, distributed processing was used. But traditional distributed methods cannot do this well and in a timely manner. Instead, we use cloud-based processing. Cloud service can perform heavy processing on big data in real-time [7–9]. In the following, we describe some relevant studies.

Sagar et al. [10] propose an intelligent system for parking cars in parking lots. This system uses image processing to detect the faces of people who are authorized to park there, such as employees of a company or residents of a building. After detecting the face, the mobile application provides more details about empty parking spaces to the person. Sharma et al. [11] conduct research on forest fire detection using image processing. They achieved good results in monitoring and detecting forest fires using early detection methods by image processing. A power source must provide the system's energy requirements continuously. In the traditional method, satellite monitoring is used to detect forest fires, which has not yielded desirable results due to the long time it takes to scan images and the low quality of the images. They use Internet of Things (IoT) devices and a sensor network in their research. Sensors inside the network communicate with each other using radio frequency (RF). With the help of IoT technology, data such as smoke, humidity, temperature, etc. can be collected from the environment and processed instantly, and the resulting information is sent immediately to the main communication nodes. The processing unit in this system includes an algorithm that detects flames or smoke by implementing the RGB and YCbCr models and creates a fire alert. Siddharth et al. [12] work on traffic monitoring and anomaly detection using image processing. They use various methods and algorithms in different parts of their research. Event detection and direction anomaly detection are two important aspects in controlling intelligent traffic in smart cities. In this research, more focus is on detecting the path of a vehicle and tracking it. For this purpose, the vehicle must first be detected in the first video frame. This detection is done by using background subtraction and combining different methods. The system works accurately both during the day and at night.

After detecting a vehicle, its tracking is performed in the subsequent frames. The vehicle and road area are identified by background subtraction. Then, with the help of morphology methods, the shape of the vehicle is identified, and a path is determined for it. In the following frames, by tracking this vehicle within the allowed road area and comparing it with the allowed path, any abnormalities are detected. This research can currently be developed in European and American countries, as they have already conducted work in this area and have infrastructure for it. Overall, this method can reduce the rate of accidents. In a country like India, traffic control and monitoring are still done manually, and the rate of human mistakes in this method is high. As a result, the number of accidents is also high. This research can be implemented in these countries in the future.

Mehboob et al. [13] propose an algorithm for transforming three-dimensional traffic video content into a Google map. Glyph-based representation with temporal tagging in surveillance videos in the open space is used for this algorithm, which can be used for event-aware detection. Memos et al. [14] propose an algorithm for a media-based monitoring system to improve the security and privacy of wireless sensor networks in the Internet of Things (IoT) network for smart city frameworks. Hoang et al. [15] attempt to diagnose cancer and other similar diseases by scanning whole slide images using the MapReduce processing model. Scanning the whole slide images at once can be efficient, but before this research, it had not happened due to the high volume of the whole slide images. They accomplished this task with image processing using the MapReduce method, which has application in diagnosing cancer and important diseases from images. Digital scanners can quickly produce high-resolution whole slide images. However, processing such complex images is computationally intensive. For example, the segmentation of a single image can result in the generation of millions of nuclei, which can take hours on a desktop computer. For a typical research project with thousands of images, this task may take weeks. Therefore, we need more processing resources such as distributed processing and cloud computing.

In this study, Hong et al. [15] presented a high-performance image analysis framework for whole slide images based on the MapReduce algorithm and a nuclear segmentation algorithm that is highly scalable and cost-effective. An overlapping segmentation method is used to divide whole slide images into extended tiles with a buffer zone. Core regions are created from segmentation with a fixed size, i.e., the entire space is divided into equal tiles. Each central region is expanded with the help of a buffer. Image processing is performed on each of these expanded tiles. White et al. [16] examin the applications of MapReduce in data mining in their research. This study focuses on the applications of the MapReduce processing model and common design patterns, and is useful for those who have little knowledge about this method. This research discusses high-level theories and low-level implementations of various computer algorithms. Algorithms such as classifier training, sliding windows, clustering, bag-of-features, background subtraction, and image registration are discussed. Heikkinen et al. [17] designed an image processing system using MapReduce, which utilizes a scalable solution for video analysis. This research focused solely on face detection and concluded that Hadoop is a suitable solution for processing such data.

Pereira et al. [18] believe that video processing applications consume resources heavily and involve a large amount of data, leading to computational complexity. They propose an architecture to increase efficiency in video processing, which is inspired by the MapReduce pattern. This approach uses map and reduce to reduce video encoding time. Duan et al. [19] discuss a standard for future deep feature encoding for managing large-scale AI-based video analytics, techniques, existing standards, and potential solutions for large-scale video analysis for deep neural network models. Their article focuses on deep learning with neural network models. Tian et al. [20] propose a background modeling algorithm at the block level to support a long-term reference structure for efficient video surveillance coding and a rate-distortion optimization for the supervision source algorithm for processing large video data in a smart city. Their research focuses on a block-level background modeling algorithm. Jin et al. [21] presented optimization algorithms and scheduling strategies based on clusters of unmanned aerial vehicles (UAVs). Rodriguez-Silva et al. [22] propose a traditional cloud-based video surveillance architecture based on a cloud processing server, a cloud storage server, and a web server. They stored a video in Amazon S3 memory and did not mention any smart city or intelligent city software. Shao et al. [23] present an intelligent processing and utilization solution for large-scale video surveillance data based on event detection and alert messages from front-end smart cameras. They do not use MapReduce and did not mention any smart city software.

Nasir et al. [24] present fog computing based resource-e_cient distributed video summarization over a multi-region fog computing paradigm for IoT-assisted smart cities. They work with a fog-based system, use Spark, and do not refer to smart city middleware. Calavia et al. [25] propose an intelligent video surveillance system that can identify abnormal and alarming situations by analyzing object movements in smart cities. The translation is based on ontology. No mention is made of smart city software, nor is there any reference to the use of cloud computing. Hussain et al. [26] present a study on allocation of virtual machine resources to support video surveillance operating systems using Amazon web services for linear programming formulas with migration control and simulation. They focus on cloud computing. Their work deals with MapReduce, scalable video streaming, and has no involvement with smart city software. Lin et al. [27] propose a cloud-based video recording system. A digital video recorder and network video recorder is proposed with their methodology. Their distributed replication mechanism uses the Hadoop distributed file system and manages the deployment design of public and private/hybrid clouds. They focus on the video recording system and have no involvement with image processing for object detection.

Wu et al. [28] proposed a peer-to-peer architecture system with a Hadoop distributed file system to avoid bottlenecks. Their approach involves a novel transmission scheme and a block-based approach. They focus on the transmission of video data and do not deal with smart city software or cloud computing. Janakiramaiah et al. [29] present an intelligent video surveillance framework using a deep learning algorithm with convolutional neural networks. Their framework is not a general goal framework for a smart city, and their paper focuses on the deep learning algorithm with convolutional neural networks. Xu et al. [30] present their approach to detecting unusual visual events in smart city surveillance using edge computing, multi-sample learning, and a unified moving average autoregressive model. They do not mention any smart city software, use edge computing, and deal with detecting unusual visual events.

In this article, we first present an architecture of a smart city, of which our proposed platform is a part. Then we describe its components and connections. Our proposed platform communicates well with the other elements in the smart city and can process video images. This system is capable of facial recognition, object detection, and behavior analysis. Other Related articles do not mention any smart city in their research. Our work is implemented in a smart city architecture and can be used for variety of applications.

The structure of the article is as follows: In section 3, we present an architecture for a smart city on which we intend to implement our platform and provide an overview of it. We describe each layer of this architecture. In section 4, the sub-layers of the middle layer (processing layer) on which our platform will be implemented are explained in detail. In section 5 we explain about MapReduce model in general. In section 6 the proposed image processing by MapReduce model is explained and in section 7 the cloud computing engine is shown in a smart city that we implement our platform.

III. Overview of the Proposed Image Processing Platform in the Smart City Architecture

In a smart city, various services are provided to citizens that they can benefit from. Our proposed platform has a general aspect, meaning it is not just for a specific purpose and can be used in various services. Some of the services provided to citizens include smart traffic control, smart control of city waste bins and waste management, smart control of water distribution, smart management of problems such as theft, smart management of missing persons, smart health monitoring services, smart pharmacy management system, smart fire supervision and management, smart management of road accidents, and many other cases.

In some studies, only one of these services has been focused on. For example, Hoang et al. [15] has worked on diagnosing cancer and other important diseases using full-slide image processing. This issue only concerned with health care. But our proposed system is actually the architecture and operation of an image processing system embedded in a smart city architecture that can be used in all services. Here we present an overview of the proposed platform within the smart city architecture, which consists of three separate layers: application layer, processing layer, and infrastructure layer. you can see the overall architecture of a smart city in Fig. 1.

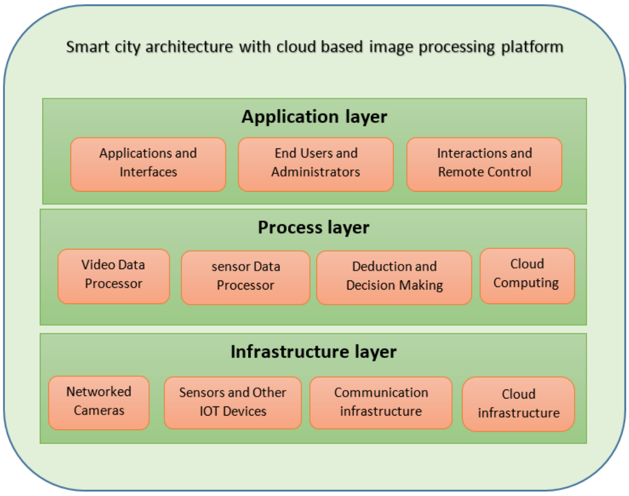

Fig. 1. Architecture of a smart city concluding our proposed image processing platform

A. Infrastructure Layer

Let's start from the lowest level, the infrastructure layer. The required equipment and infrastructure are located in this layer. The cloud computing Infrastructure is also located in this layer. The cloud may be local (domestic) or Foreign. Data collection is also done in the infrastructure layer and through a large number of sensors, cameras, and sensor networks. This layer supports various types of Internet of Things devices. As we mentioned before, IoT devices and sensors are used to make various parts of the city smart. For example, consider a fire detection system in a building. In a smart city, all buildings must be equipped with such a system to inform building occupants and firefighters in case of fire. Smoke and temperature detection sensors are used for this purpose, and camera data is also used to detect flames or smoke. So, only a few sensors and cameras are used for fire detection in a single building. If we consider the entire city, the number of these devices becomes very large. The data received from these devices is a stream and does not stop. This data needs to be processed and a result must be obtained whether there is a fire or smoke in the building or not. These devices are located in the infrastructure layer and collect the necessary data for the system. Cloud infrastructure is also located in this layer.

B. Processing Layer

The middle layer, called the processing layer, actually performs data processing, extracts valuable information, and decides on performing a specific action. Raw data is placed under cloud-based processing in this layer. For example, if the received temperature from a section of a building is 50 degrees Celsius, it does not indicate anything specific. But when this data and other accompanying data such as smoke concentration and received video from the processing site are placed together, we can understand what is happening. If the smoke concentration is higher than the permissible limit and smoke or flame is detected in the received images, it can be said that a fire has occurred, and this is precisely the meaning of data processing. Then, the deduction and decision-making unit decides which alarms to generate and send alerts to whom. Since we are dealing with big data in this system, we cannot use an ordinary server. Because we need high storage and processing resources. A cloud-based system that utilizes distributed computing is a reliable option for implementing such a system in a smart city. Yoon et al [32] has developed A sample smart city called U-city or Utopia [31]. In this article, we can include any smart city in this architecture, including Utopia However, it is done to be implemented in smart cities of Iraq, but any smart city with a similar architecture and components can use this platform. In a smart city, sensors and cameras are connected to each other through communication technologies and ICT. Providing high-speed communication infrastructure helps develop smart cities. If the bandwidth and internet speed are low, IoT devices cannot efficiently send their information, which leads to inefficient services in a smart city.

The processing layer is very important to us because it includes the platform that we propose for image processing in a smart city. This layer processes the data and makes decisions about events. This layer is divided into sub-layers, which are the main topic of our work. The data collected in the infrastructure layer is managed and processed in the processing layer. Data needs to be simplified and reduced in size because they are always in the flow and need to be processed in real-time. Models such as MapReduce, Spark, Storm, Flink, and any suitable data streaming model can be used for processing. We use the MapReduce model in this research.

C. Application Layer

In the application layer, end users such as citizens, city observers, controllers and managers of urban services, as well as smart city applications are located. This layer establishes communication between end users and the smart city monitoring system and its services. For example, various applications are created for traffic monitoring and control, some of which are useful for citizens and some for traffic observers. All of these applications establish communication between the citizen or observer and a part of the smart city that is related to traffic control, and also provide services to them. In fact, this layer acts as an interface.

IV. Sublayers of the Processing Layer for Video Surveillance in Smart Cities

The processing layer in smart cities processes data from cameras, sensors, and other potential IoT devices. Since our research is about image processing in smart cities, we do not consider processing other data, and we have only shown the components of this layer in Fig. 2 briefly.

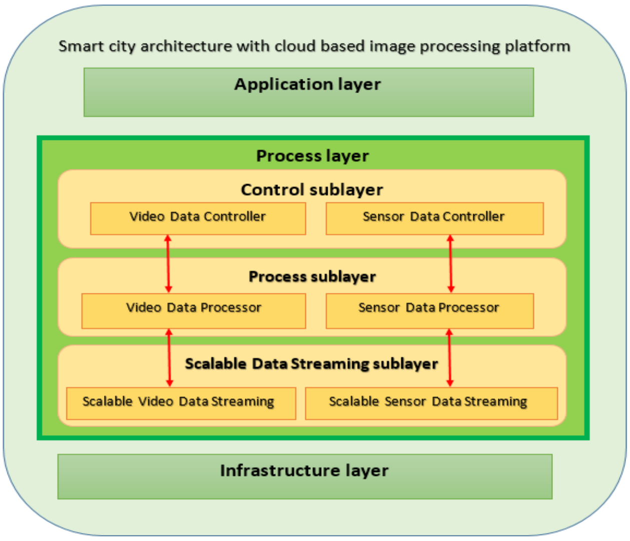

Fig. 2. Sublayers of processing layer in a smart city architecture consisting our proposed cloud-based platform of image processing

The processing layer consists of three sub-layers as you can see in Fig. 2:

- The control sublayer includes a video data control section and a sensor data control section.
- The processing sublayer includes a video image processor section and a sensor data processing section.
- The scalable data streaming sublayer includes scalable sensor data streaming unit and scalable video streaming unit.

Note that each sublayer consists of two sections, one related to video data and one related to sensor data in the smart city. This separation is because the operations performed on sensor data are different from those performed on video data due to their different nature. In the following, we will explain the three sections related to video data in the three sublayers of the process layer.

A. Video Control Section in the Control Sublayer

This section has four parts, each with a specific responsibility.

- The camera control section: It monitors and controls the cameras in the smart city to ensure they are functioning properly. For example, if a camera loses power for any reason and goes offline, the camera control section will detect this and address the issue.
- Control section of the image processor: This section supervises image processing in the processing layer to ensure that it works properly.
- Storage Control Section: It monitors the information storage section.
- Communication Control Section: It monitors the video data flow to ensure that communication between the processing layer and the infrastructure layer is established and that there are no issues with video transfer.

B. Video Data Processor in the Process Sublayer

This section has two units and a storage:

- Processor or MapReducer is a unit for image processing that processes images in two phases of mapping and reducing. The working mechanism of the image processor using the MapReducer model will be explained in detail in the ... section.
- The Streaming Receiver, which receives video data from the Scalable data streaming layer and stores it in HDFS, is composed of four components: Network interface, Buffer, Decoder, and Feedback control.

C. Scalable Video Streaming Section in the Scalable Data Streaming Sublayer

This section also consists of several parts that work together.

- Network Interface: Facilitates communication between different network components.
- Stream Manager: Monitors network bandwidth in real-time and packetizes encoded data.
- Media Encoder: Encodes video data from cameras in the smart city. For adaptable data stream, live video data are encoded with a specified QP value by this section.
- Bit-stream Extractor: After encoding, video data is handed over to this section and then transferred to the Stream Manager to be packetized. Finally, packets are separated for adaptation to different network conditions.
- Networked Channel Bandwidth Monitor: This section evaluates the network bandwidth and communicates with the Quantization Parameter changer unit to control the encoding rate based on the pre-determined QP value.
- Quantization Parameter changer: provides the guidelines and parameters required for encoding.

What We explained is Our proposed platform for image processing in smart cities of Iraq. You can see This platform with its components in detail in the Fig. 3.

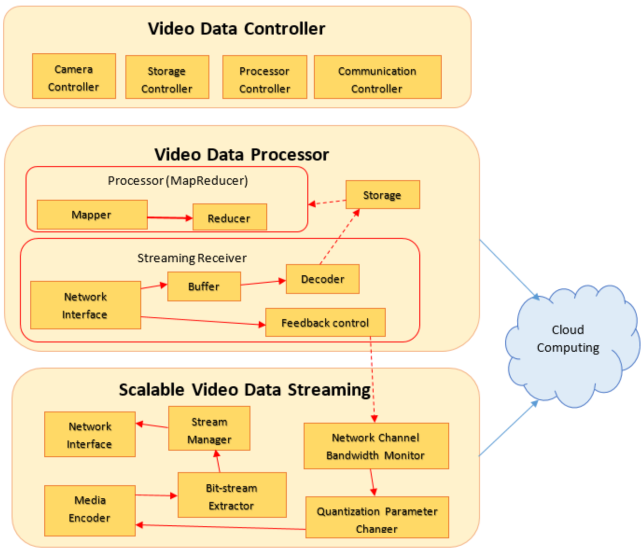

Fig. 3. Our proposed cloud-based platform and its components

In a smart city, camera data is encoded in a way that the instructions and parameters of this process are received from the Quantization Parameter changer. This unit encodes data with various values based on the information obtained from the Network Channel Bandwidth Monitor. The bandwidth of the data stream receiver, the strength of radio wave signals, and a feedback signal are the three factors used to determine the network bandwidth in real-time. When initializing, the scalable video streaming unit sends a message to the stream receiver, and that unit responds with an available bandwidth. The stream receiver realizes that the bandwidth is in good condition by receiving a strong signal. If it receives a weak signal, it understands that the bandwidth is weak. The Networked Channel Bandwidth Monitor continuously monitors the network status and evaluates the available bandwidth. It also communicates with the Quantization Parameter changer to control the encoding rate based on a predetermined Quantization Parameter value.

For adaptive live network streaming, live video data is encoded with the QP value determined by Media Encoder unit. After encoding, the encoded video data is transferred to the Bit-Stream Extractor unit and the Stream Manager unit, which packetizes the data appropriately. Finally, the data packets are separated to adapt to different network conditions.

V. MapReduce Processing Model

HDFS is a distributed file system specific to Hadoop that uses the surrounding space of a cluster to store data. Therefore, it seems that the volume is continuously increasing, and the produce redundancy prevents data loss [31]. This distributed file system also allows data collectors to empty their data into HDFS to be used in MapReduce processing model. The MapReduce model consists of two parts: the mapping phase and the reducing phase. Other steps can also be added in between, such as before or between mapping and reducing. The mapping phase reads a cluster of data, performs operations on it, and ultimately outputs pairs of values and their keys (Key-value). The mapping phase is also known as the partitioning phase. The output of mapping is then fed into the reducing phase. Reducers take the output of the previous stage, the pairs of key-value, and after performing operations to aggregate the values, they output the reduced result. A simplified form of the mapping and reducing process is shown in Fig. 4.

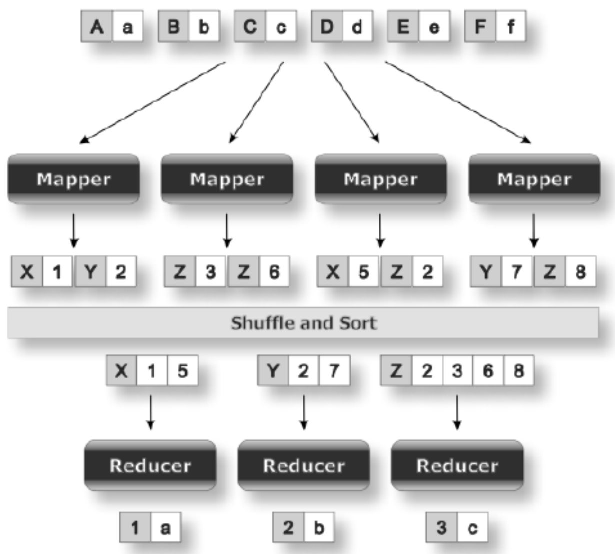

Fig. 4. The MapReduce processing model workflow [32]

VI. Image Processing by MapReduce Model

Each segment of video data that is input to the MapReduce engine is in the form of <video path, offset> input values. In other words, in the first step, video input data is divided based on a static offset. This value is transformed into the pair <video ID, analyzed data> in the mapping engine. The output of the mapping phase is then fed into the reducing phase. In this phase, the reducing operation is also performed on it, and the final output is in the form of <video ID, list (analyzed data)>. You can see MapReduce on video data in the Fig. 5.

Our proposed platform can perform object detection, object tracking, object recognition, and behavior analysis by using the MapReduce distributed processing model. This can be used in various smart city applications. For example, license plate recognition is one of the most common types of object recognition in image processing. In a smart city, this capability is certainly needed for intelligent traffic control. For example, if a car passes through a red light, with immediate license plate recognition, a fine or warning can be sent to the driver's phone.

As another example, by detecting a car on the road at two predetermined locations with a specific distance, the speed of the car can be calculated, and if it exceeds the legal speed limit, the driver can be fined. Facial recognition is another application of image processing. This can be used for the entry and exit of employees or residents of a building. For example, instead of employees registering their fingerprint every day, they can pass in front of a camera and the camera can identify their faces. There are many applications of cloud-based image processing in a smart city.

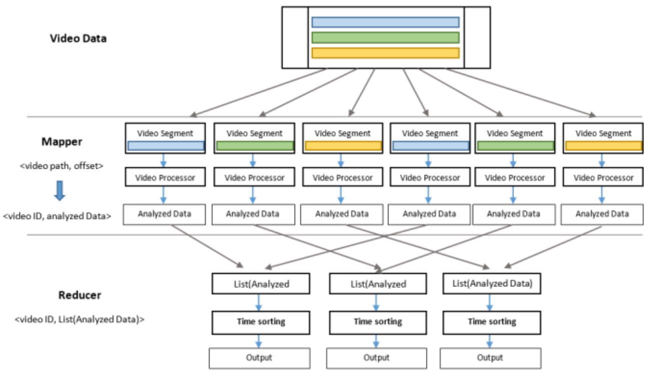

Fig. 5. The video data processing by MapReduce model

In the first step, the input video data is divided into groups based on a fixed length of group-of-pictures (GOP) using static offset. When video data is stored, it is usually compressed using a codec. The group-of-pictures (GOP) includes a key image frame and a non-key image frame. A key frame is a frame that is retrieved independently and without reference to other frames, also known as an Infra Frame (I-frame). A non-key frame only contains information created from the difference between the current frame and the previous I-frame.

If GOP is not considered during the division of video data, the I-frame data, which is a key frame, will be lost, and the data of other frames, which refer to key frames, will not be readable. As a result, video data will be damaged. It is possible to recover the compressed file and then divide it, but this is inefficient because the encoding process takes a very long time. Therefore, it is better to consider GOP from the beginning. In the partitioning, the key-value pairs of the information path of each partition are divided, and the offset is provided to the mapper. In the second step, the Mapper produces an output in key-value pairs of "video ID" and "analyzed data". The intermediate data is sorted based on the "video ID". Finally, the Reducer receives the key-value pair of "video ID, list (analyzed data)" and sorts the analyzed data based on time and writes the output to HDFS. You can see these steps in detail in Table 1.

TABLE I. Map and Reduce steps and the key-value pairs each step use in our platform [31]

step	Input/output	(key, Value)	Operation
Mapper	input	(video path, offset)	Divides the input video and processes the divided parts
	output	(video ID, analyzed data)	
Reducer	input	(video ID, List analyzed data)	Integrate and sorts the analyzed data by time

VII. The Cloud Computing Infrastructure

The cloud computing infrastructure is located in the infrastructure layer. This cloud can be local (domestic cloud) or outside the smart city (foreign cloud), because sometimes the local cloud may not be able to respond to the high demand of the image processing system or face a problem. For such situations, the cloud infrastructure outside the smart city must be considered in advance. The processing layer communicates with the infrastructure layer and is connected to the cloud to perform the necessary processing. In fact, it rents out its cloud-based computing resources to the smart city. Programmers determine their required computing power to be able to use it. Sometimes, during an operation, the required computing power may dynamically change and not be constant, which is taken into account in cloud processing. As we mentioned before, cloud computing resources can be local (domestic) or outside the smart city infrastructure (foreign). You can see the layers of cloud computing used for a smart city in our platform in Fig. 6.

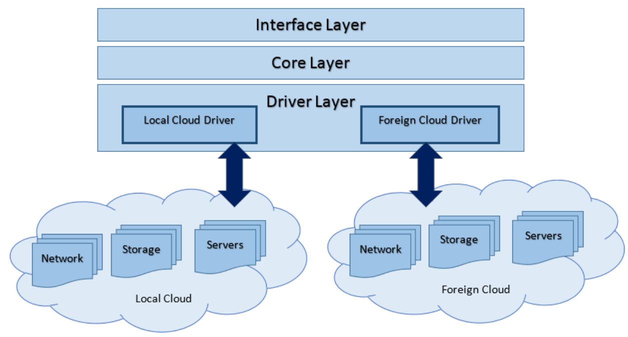

Fig. 6. Layers of a cloud used for smart cities in our platform [31]

VIII. Statistic Results and Discussions

This research aimed to investigate the factors affecting the acceptance of the proposed new technology, a cloud-based image processing platform for the smartening of different parts of the management, monitoring and control of smart cities in Iraq, by using the UTAUT model.

A. *Research Design and Data Collection*

In this research, quantitative research method and Structural Equation Modeling (SEM) were used to validate the proposed hypotheses and confirm our proposed conceptual framework. Since this study included 25 observable variables, the minimum sample size is 5 ×21=105. The Data were collected from a fillable online questionnaire converted to a Google Form format. The questionnaire link was distributed to the target population of respondents and after data collection and screening, a total of 135 valid surveys were collected for analysis.

The questionnaire consisted of two parts. The first part was concerned with the demographic and behavioral information of the respondents. The second part was concerned with the measurement information based on the proposed model. Items were measured on a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5). In the proposed model, the independent variables include four major characteristics: performance expectation (PE) five items, effort expectancy (EE) four items, social influence (SI) four items and facilitating conditions (FC) four items. The dependent variable consists of one characteristic: behavioral intention (BI) four items. There were total of 21 measurement items and the details of each section are available in Table 2. The hypotheses are as follows:

H1. Performance Expectancy (PE) significantly influences Behavioral Intention (BI) to use the cloud-based image processing platform for the smartening of different parts of the management, monitoring and control of smart cities in Iraq.

H2. Effort Expectancy (EE) significantly influences Behavioral Intention (BI) to use the cloud-based image processing platform for the smartening of different parts of the management, monitoring and control of smart cities in Iraq.

H3. Social Influence (SI) significantly influences Behavioral Intention (BI) to use the cloud-based image processing platform for the smartening of different parts of the management, monitoring and control of smart cities in Iraq.

H4. Facilitating Conditions (FC) significantly influences Behavioral Intention (BI) to use the cloud-based image processing platform for the smartening of different parts of the management, monitoring and control of smart cities in Iraq.

TABLE II. THE DETAILS OF CONSTRUCTS, ITEMS, AND OBSERVED VARIABLES IN THE STUDY

Constructs	Items	Observed Variables
Performance Expectancy (PE)	PE1	The use of cloud-based image processing platform helps to improve performance in the management and control of the different parts of smart cities in Iraq.
	PE2	Using the cloud-based image processing platform, the social and environmental effects and benefits of smart urban services in Iraq can be measured.
	PE3	Using the cloud-based image processing platform can increase the chances of achieving management goals in the different parts of Iraq's smart cities.
	PE4	Using the cloud-based image processing platform can help improve the quality of information in the management and control of the different parts of Iraq's smart cities.
	PE5	Using the cloud-based image processing platform in the management and control of different parts of Iraq's smart cities will lead to providing more effective services.
Effort Expectancy (EE)	EE1	It is easy to learn to use the cloud-based image processing platform in managing and controlling different parts of smart cities in Iraq.
	EE2	It is easy to become proficient in using the cloud-based image processing platform to manage and control the different parts of Iraq's smart cities.
	EE3	It is expected that the use of the cloud-based image processing platform in the management and control of the different parts of Iraq's smart cities will be clear and understandable.
	EE4	Using the cloud-based image processing platform in the management and control of the different parts of Iraq's smart cities saves time in providing urban services.
Social Influence (SI)	SI1	The Iraqi government's support of the cloud-based image processing platform in managing and controlling the different parts of smart cities to evaluate urban services helps to improve the quality of life.
	SI2	The governing laws regarding the use of the cloud-based image processing platform in the management and control of the different parts of Iraq's smart cities contribute significantly to the evolution of service delivery.
	SI3	Iraqi government policies and plans are affected by the use of the cloud-based image processing platform to manage and control the different parts of smart cities.
	SI4	Iraqi urban management experts consider it appropriate to use the cloud-based image processing platform in the management and control of the different parts of smart cities.
Facilitating Conditions (FC)	FC1	There is the necessary knowledge to use the cloud-based image processing platform to intelligently manage and control the different parts of Iraq's smart cities.
	FC2	There are specific individuals or groups available who can help with the issues and problems of using the cloud-based image processing platform to manage and control different parts of smart cities in Iraq.
	FC3	There are the necessary resources to use the cloud-based image processing platform to intelligently manage and control the different parts of Iraq's smart cities.
	FC4	There is the sufficient experience to use the cloud-based image processing platform to intelligently manage and control the different parts of Iraq's smart cities.
Behavioral Intention (BI)	BI1	Organizations and departments in Iraq intend to use the cloud-based image processing platform in the near future for the intelligent management and control of services in smart cities.
	BI2	Organizations and departments in Iraq are intent to use the cloud-based image processing platform in the near future for intelligent management and control of services in smart cities.
	BI3	Organizations and departments in Iraq have planned to use the cloud-based image processing platform for intelligent management and control of services in smart cities.
	BI4	When there is a serious need for intelligent management and control of services in Iraq's smart cities, the cloud-based image processing platform will be used.

B. Descriptive Statistic Results

The majority of respondents were males (55.6 %) working in government fields (57.0 %). Also, the majority of the respondents (45.9 %) were aged between 31 to 40 years with a postgraduate education level (54.1 %). The demographic profiles are detailed in Table 3.

TABLE III. DESCRIPTIVE STATISTICS

Item	Description	Sample	%
Gender	Male	75	55.6
	Female	60	44.4
Age	Less than 30	25	18.6
	31 - 40	62	45.9
	41 - 50	42	31.1
	Above 50	6	4.4
Education	Below Undergraduate	11	8.1
	Undergraduate	51	37.8
	Post Undergraduate	73	54.1
Occupation	Government Worker	77	57
	Private Company Worker	46	34.1
	Joint worker	12	8.9

C. Structural Model and Hypotheses Testing

For the hypothesis testing, firstly a model of measurement was tested via confirmatory factor analysis (CFA). The validity of the hypothesis test is to observe a set of hidden variables that should be measured theoretically. The outcomes confirmed a total of 20 items which include PE (five items), EE (four items), SI (three items), FC (four items), BI (four items). one item was deleted since the standardized item loading was less than 0.5. Cronbach's outcome for the instrument was 0.948. The findings of the hypothesized path model show a good fit with the data. Hypothesis testing results in Table 4 showed the significance of four hypotheses.

TABLE IV. STRUCTURAL PARAMETER ESTIMATES

Hypotheses	Relationship	Estimate (b)	Result
H_1	PE →BI	0.858	Accepted
H_2	EE →BI	0.859	Accepted
H_3	SI →BI	0.805	Accepted
H_4	FC →BI	0.764	Accepted

The correlation between performance expectancy (PE) and behavioral intention (BI) was supported (H1: b = 0.858, t-value = 19.274, sig < 0.05). H2 assumed that effort expectancy (EE) significantly impacts behavioral intention (BI), which was also supported (H2: b = 0.859, t-value = 19.337, sig < 0.05). H3 postulated that social influence (SI) had significant impacts on behavioral intention (BI) which was also supported (H3: b = 0.805, t-value = 15.649, sig < 0.05). The correlation between facilitating conditions (FC) and behavioral intention (BI) was also supported (H4: b = 0.764, t-value = 13.649, sig < 0.05).

IX. CONCLUSION

This study considered factors influencing cloud-based image processing platform admission for management purposes of the different parts of smart cities in Iraq. Per the UTUAT model, the empirical data of 135 respondents exhibited that 4 factors, performance and effort expectancies, social influence and facilitating conditions, have a impactful effect on behavior intention. When evaluating factor loadings of each construct on behavior intentions, we understood that performance and effort expectancies had the strongest effects on behavior intention. This study increases the present research knowledge of the UTAUT model since there are very restricted researches on cloud-based image processing platform adoption for management purposes in Iraq.

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