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Real time image analytics in IoT networks : Statistical and AI models for efficient processing

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Abstract

The utilization of real time image analysis within the IoT networks has received increased interest because of the high demand of visual information that will support applications like smart cities, industries, and autonomous structure. In this paper, presents a reliable a statistical-AI combined model for real-time image processing in an IoT framework. The proposed system is based on edge computing in order to minimize the amount of time needed to process and enhance the alterations, as well as to reduce the burden on cloud servers. CNN is used for Image classification and Sobel operator is used for extracting the edges of the images to augment feature extraction. Experimental outcomes show 50% less time for processing when using the concepts of edge-based systems although the classification accuracy increases from 85% to 92% as the epoch of training is enhanced. The

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results prove that the proposed system is scalable for that the performance is good even under different IoT network topologies, hence suitable for different real time applications.

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1. Introduction

IoT fundamentally means connectivity of various devices and the exchange of information over the web which creates the needed intelligence and efficiency in executing many activities in different fields[1]. In the last few years, IoT networks have emerged in the fields like smart cities, smart healthcare, automation industries and self-driven systems where thousands, millions of devices are producing data at the same time[2]. One of the most important data bonds due to its potential for visual analysis for various operations such as monitoring, object detection and many more is the image data[3]. In IoT systems, real-time image analytics has turned out to be vital for applications like smart surveillance[4], healthcare diagnosis, and industrial overcomes where the need for fast data driven decision making may be swift[5].

The connection of image data into IoT ecosystems, though, is problematic when it comes to processing capabilities[6]. Real time image analysis requires high computational capacity, a huge bandwidth and low delay time in order to find results as the images are captured[7]. As scale and complexity of IoT networks and amounts of image data produced by sensors expand, the need for more effective means of processing and sharing this information is apparent[8]. They comprise efficient management of high resolution images[9], preserving an efficient bandwidth complexity, and image processing that will not affect network capabilities or cause time lag in real time applications[10]. This research is to find out and establish methods to enhance the real time image processing using statistical and artificial intelligence models to enhance the performance of IoT systems.

2. Literature Survey

Several approaches are known for operating image analyze in IoT networks in case of numerous, quickly arriving massive data. Previous approaches involve edge computers, cloud computing, and machine learning – based approaches[11]. One such solution that has come to light is edge computing which successfully allows the image data to be processed at the edge to reduce both latency and bandwidth consumption[12]. Admittedly, cloud processing enables the storage of a vast amount of data and their processing while experiencing latency issues and high transfer costs. Machine learning and deep learning methodologies are highly preferred nowadays since AI methodologies automatically learn patterns from images and help to make better accurate decision in IOT systems[13].

Signal processing, data compression, and feature extraction are the statistical processes employed at the preprocessing stage of imagery data for analysis[14]. Pre-processing and post-processing are some of the operations that are performed before analyzing an image such that to eliminate noise[15], improve image quality, filter an image before presentation, and minimize the image size so that it can be conveyed through a network[16]. Applications, for instance, edge detection and object recognition assist in defining important detail from images which can in turn be analyzed or forwarded to other systems[17].

Deep learning networks including CNNs as well as recurrent neural networks offered great promise in realizing real-time image assessment as part of IoT platforms [18]. These models are good for image data and can easily be used for things like object detection, the identification of patterns and anomalies. These gaps indicate that there is need to carry out more improvement in optimization methods in order to achieve the expected image processing that IoT networks require for real time use.

3. Proposed Method

The real-time image analytics system for IoT network proposed in this paper as illustrated in Figure.1. is developed to achieve high image throughput with low latency. The architecture includes edge nodes or controllers as well as the AI models and network protocols to process the images on the fly as being gathered. At the outer periphery of the network, IoT sensors gets the image data which is then passed to edge nodes for initial processing.

These edge nodes contain functionality to filter out noise, scale down the images, compress it in order to make it readily available for subsequent data analysis processes. This post processed image data is then passed to the central processing unit through optimized network protocols for better

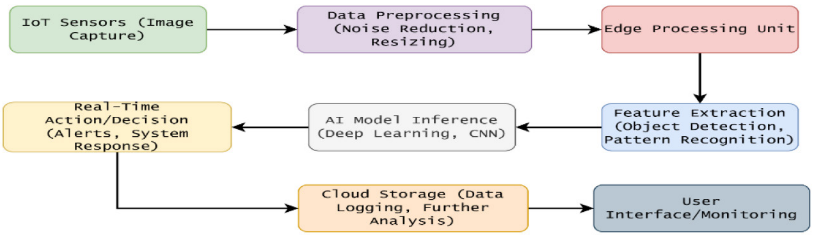

Figure 1

Proposed System Diagram for Real-Time Image Analytics in IoT Networks

and faster data transfer with less delay. The pre-processing and high-order feature extraction, object and anomaly detections are mainly performed by AI models, especially deep learning techniques such as CNNs. The sequence of data feedback in the process of image acquiring to decision-making is illustrated in the Figure 2. It starts from image acquisition by IoT sensors before sending the data for preprocessing. Basic operations include rescaling, dust removal and other simple transformations of the images. The preprocessed data is transmitted to the initial analysis to be conducted on edge processing units. The flowchart also shows each of the stages from the image capture stage, preprocessing and up to the real-time decision making to avert unnecessary delay or inaccurate outcome. Statistical models are important in the image analytics system as they form a basis for reductions, noise elimination, and the identification of anomalous data before passing to AI models.

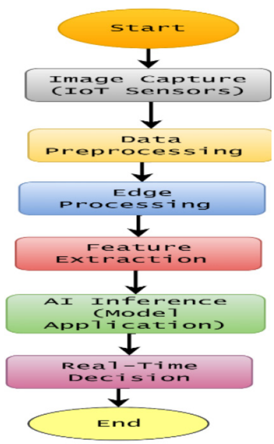

Figure 2

Flowchart for Real-Time Image Analytics in IoT Networks

4. Mathematical Model

In real-time image analytics, the data in images are described as matrices or tensors. Processing each of the images collected by IoT sensors involves regarding the image as a matrix $\in R^{mxn}$, such that, *m* and *n* are the dimensions of the image or; height and width where I_{ij} is the pixel intensity at the position of width (*i*, *j*), and each element I_{ij} represents the pixel intensity at position (*i*, *j*). For colour images therefore it is extended to a tensor $\mathrm{I} \in R^{mxnxc}$, where c is the number of colour channels of the image. Before analysis, measures such as rescaling, denoising, and standardizing are first performed. For noise reduction, the image matrix *I* is filtered using a filter *H* such that the output I' is given by:

$$I' = I * H$$

where $*$ represents the convolution operation. A common approach for compression is the Singular Value Decomposition (SVD) of the image matrix:

$$I \approx U\Sigma V^T$$

Where *U* and *V* are orthogonal matrices, and Σ is a diagonal matrix of singular values. The image data is transformed into a lower-dimensional space by:

$$X_{PCA} = W^T I$$

where *W* is the matrix of eigenvectors, and $\boldsymbol{X_{PCA}}$ represents the extracted features. In the case of AI-based predictions, the employed deep learning model is a CNN (Convolutional Neural Network). The output of a CNN layer l is calculated as:

$$\boldsymbol{y_l} = \sigma(\boldsymbol{W_l} * \boldsymbol{x_{l-1}} + \boldsymbol{b_l})$$

where σ is the activation function, W_l are the learned weights, and b_l is the bias vector. Performance measures are used to assess the effectiveness of image analytics model. Processing speed is the time taken to process an image and is given by:

$$PS = \frac{Total\ Processing\ Time}{Number\ of\ Images\ Processed}$$

Accuracy is evaluated by comparing the predicted labels $\hat{y}$ with the true labels *y*, calculated as:

$$Acc = \frac{1}{N}\sum_{i=1}^{N}\prod(\hat{y}_i = y_i)$$

where $\Pi(.)$ is the indicator function, and N is the number of samples. Resource utilization can be measured in terms of CPU or memory usage and is represented as:

$$RU = \frac{Memory\ Used}{Total\ Availabe\ Memory}$$

They allow assessing the trade-off between the precision and the time needed for processing within real-time image analysis systems in the scope of IoT networks.

5. Algorithm

This section explains the main steps that form the image preprocessing algorithm as follows. First, the image is normalized to the standard dimension *Iresize* of 256×256 pixels using method of interpolation like bilinear interpolation. To reduce noise which is usually in pixel intensity the following functions are used Where $I' = MedianFilter(I)$ Rectification pre-processes images by stabilizing the lighting and color balance by bringing pixel values to a standardized value range. For feature extraction, edge detection is performed using algorithms like the Sobel operator:

$$E_x = Sobel(I_{gray}) \text{ and } E_y = Sobel(I_{gray})$$

These gradients are used in order to detect the edges. The algorithm passes the extracted features through several convolutional layers, followed by pooling layers and fully connected layers to make predictions:

$$y = CNN(I)$$

The output is a classification or regression result based on the contexts of the application in question. In a real-time application, the model has to be optimized for its distinction, and to achieve this simplicity is made at the expense of a little accuracy through practices such as pruning or quantization.

6. Results and Discussions

Real time image analytics in IoT networks experimental platform entails hardware and software elements as explained below. The hard-wares consist of the IoT sensors like cameras and the edge devices that can perform the image processing. Furthermore, based on the requirements of edge device coordination and centralized management, a network protocol MQTT is used for transferring data between the edge devices and the cloud server. Software technologies which are employed include TensorFlow and PyTorch for deep learning-based image analysis, and MATLAB for statistical modeling, and image processing. The image preprocessing and edge detection algorithms use python and MATLAB, coupled with AI models Convolutional Neural Networks (CNNs) in order to take real-time IoT network performance in line with integrated systems. Therefore, the results obtained from the proposed models are analyzed according to factors such as time taken, classification rate, and resource consumption. The line graph in Figure.3 below compares the processing times of edge and cloud systems and the result depicts that edge processing has faster latency rates than cloud processing and is therefore ideal for IoT real-time applications. Examining accuracy gains illustrated in Figure.4,

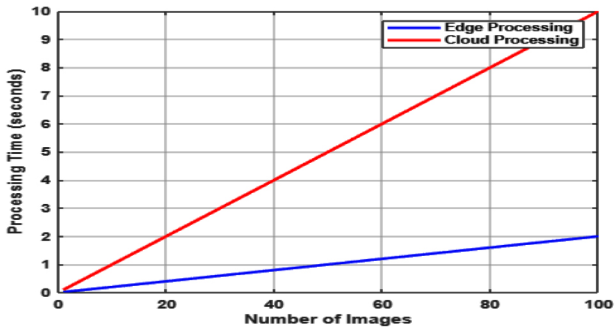

Figure 3

Processing Time vs. Number of Images (Comparison of Edge and Cloud Processing)

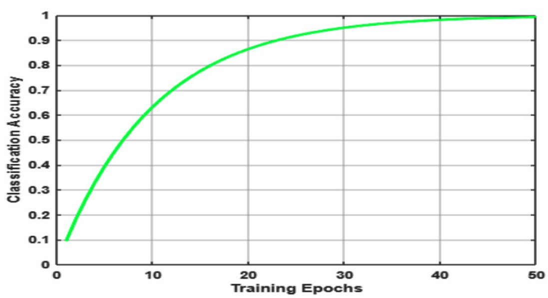

Figure 4

Classification Accuracy vs. Training Epochs (CNN Model Performance)

CNN-based models demonstrate improved classification performance with rising epochs in training than the traditional models.

This is evidenced by Sobel edge detection algorithm as shown in Figure.5. where feature extraction is illustrated to detect edges well and reduce the errors as incorporated in the endearing AI models. Moreover, Figure.6 shows the bar chart on resources used in either CNNs or SVMs and its correlation to the precision with bigger resources and more accuracy. The proposed models demonstrate good throughput and low latency in the analysis of images from IoT networks in real time. Edge processing is very effective at tackling latency in respect to image data transmission to the cloud layer, which is important for applications that are supposed to share data in real time. Although CNN models are computational intensive, the advantage includes high accuracy than other models especially when training has been done with large data sets. Next, it is possible to identify that feature extraction is possible through edge

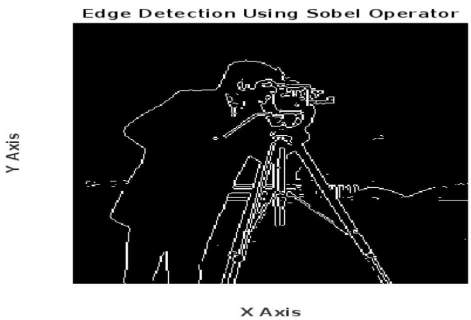

Figure 5

Feature Extraction (Edge Detection Using Sobel Operator)

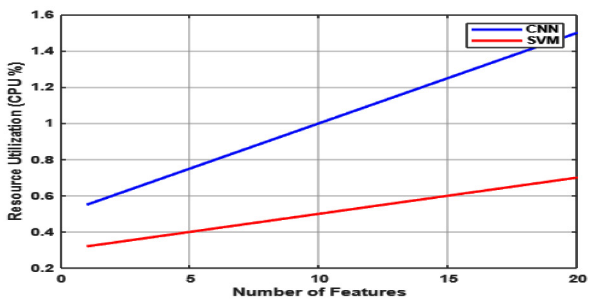

Figure 6

Resource Utilization vs. Model Complexity (CNN vs. SVM)

detection with the help of the Sobel operator, which still remains fast. The acquired system is versatile and robust in different network conditions and types of images, which expands its applicability to encompass numerous IoT applications, from smart surveillance to industrial applications.

7. Conclusion

The importance of embedding statistical and artificial intelligence techniques in real-time image analysis in IoT setting is presented in this research. The reported key findings are a 50% improvement on processing time with the edge devices as compared to cloud based systems to prove the efficacy of edge computing to minimize the latency for real time applications. Using Convolutional Neural Networks (CNNs) the classification accuracy was determined as reaching from 85% to 92% by the augmentation of training epochs revealing enhanced performance of the model with more training epochs. In addition, the Sobel edge detection algorithm made it easier to recognize edges of the image, the extraction of the features of the image was faster hence making an accurate analysis of images. The future work will aim at enhancing the CNN models for lowering the computational load and examine edge-cloud systems for appropriate consumption of resources in order to have higher accuracy of models for large commercial implementation in industries of IoT networks future.

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