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# CONTEXT-AWARE REASONING MODEL USING DEEP LEARNING AND FOG COMPUTING FOR WASTE MANAGEMENT IN IOTS ENVIRONMENTS

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**ABSTRACT**

Recently, Internet of Things (IoTs) influences every aspect of human daily lives through intelligent systems as healthcare, traffic management, and smart building. These IoTs systems depend on contextualization of collecting data through context aware system to gain knowledge by using context reasoning. context reasoning is a way for deducing knowledge and providing better understanding of the collected raw data. Context reasoning is commonly carried out at the cloud due to its high processing capabilities. However, the main challenges of using cloud are high latency time and resource consumption. To meet these challenges, Fog computing is proposed as an intermediate layer between the IoTs devices and the cloud layer to comply IoTs requirements of latency time reduction and resource consumption by deploying services to the fog layer. In this paper a new context reasoning model is proposed based on three previously defined Deep Learning (DL) models which are GoogleNet, ResNet101 and DenseNet201, the results obtained in three cases are compared in cloud and cloud/fog environments. The conducted simulation experiments with fog showed that the proposed cloud/fog model can reduce the time delay, execution time, and energy consumption with good classification accuracy which is up to 96%. These reduction values are 4%, 10%, and 94%, respectively, less than values by using cloud layer.

**Keywords:** *IoTs, Context reasoning, Waste management, Fog computing*

## 1. INTRODUCTION

Internet of Things (IoTs) [1] is a major source of big data, as it depends on connecting large number of devices through the network. IoTs promises to develop the world which all objects are connected to each other through wired or wireless network without human hands by transferring data through a network. In IoTs, data is collected using deployed sensors and different applications process this data to obtain knowledge to deliver it to actuators for performing the required actions. In addition, the objects communication and exchanging information in IoTs provide intelligent service to end user. IoTs is expected to be one of the promising areas of future technology in coming decades. Recently, IoTs applications provide intelligent services to end users, they expanded in many domains like industry environment [2] and society [3]. In such applications, every raw data is validated and preprocessed to get high level knowledge.

Waste management [4] is one of IoTs applications in smart cities. Waste management is a major concern in development countries as, growing population means increasing waste rate. In addition, waste requires set of actions management from its inception to its final disposal. This includes the collection, transport, treatment and disposal of waste, together with monitoring and regulation of the waste management process. The main challenges of waste management are collection and

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classification [5]. For waste classification, waste sorting is ought to be achieved at the earliest stage as possible, in order to maximize the amount of recycled items and reduce the possibility of being contaminated by other waste items. Moreover, waste classification requires more human power and much time, instead, classifying garbage using image processing can be a very productive way to reduce wastage rate and reduce time consumption.

The basic task of IoTs applications is intelligent learning mechanism for prediction such as classification and pattern recognition through reasoning phase [1]. In addition, deriving high level knowledge from provided context is implemented in reasoning phase. Reasoning phase includes three steps which are context preprocessing, sensor data fusion and context inference. In context preprocessing, raw data is prone to be inaccurate and incomplete so, it needs to remove outliers and fill missing values. In sensor data fusion, data is combined from different sources to yield accurate and complete information. Finally in context inference, high level context information is derived from the provided contexts. Reasoning is performed in cloud and this generates long network latency and increases resource consumption time because of physical distances. In this paper, the proposed model is applied to waste management application to solve context reasoning problem.

Furthermore, Edge/Fog computing [6] is suggested as a layer between sensing layer and cloud layer as Mobile Edge Computing (MEC) to optimize network operation. Edge computing is IoTs semantic reasoning and it is utilized to distribute tasks to IoTs reasoning devices as intelligent processing method to improve computing capabilities. Fog computing is a new pattern of deployed computing to expand the cloud to the network edge and provides security, storage, data access and computation [7]. Also, it is a distributed computing paradigm that provides connectivity for wide range of IoTs devices considering real time analytics, data security and policy restriction [8]. Fog extends the cloud to be closer to terminal device and supports low latency, large scalability and heterogeneity. Fog devices can be deployed anywhere in the network and it extends computing to the edge of the network. Shifting data analytics to fog improve the overall performance and avoiding sending vast amount of data to cloud node. The major goals of fog computing are reducing the latency and response time cost, minimizing traffic data volume and minimizing the processing cost in the cloud. In addition, Fog computing is considered to improve quality of services (QoS) in IoTs environments. QoS has some challenges such as: numerous IoTs devices means generating massive amount of data, most likely IoTs applications require real time actions and IoTs devices requirements like battery, bandwidth and storage. Fog computing is able to provide a solution to overcome these challenges and to tackle high latency problem of the cloud by allocate idle devices near users.

Machine learning is just a subset of artificial intelligence specifically that focuses on teaching an algorithm how to do task without being explicitly programmed. Deep Learning DL [20] is a subset of machine learning which takes this idea even a step further and says how automatically extract the useful pieces of information needed to inform future prediction or make a decision. The main idea of DL is how to define features from raw data. DL can build powerful computer vision systems capable of solving extraordinary complex tasks. A convolutional neural network (CNN) [20] is most popular deep learning algorithm used for image related applications. The main upgradition in CNN performance was mainly due to designing of new blocks.

In this paper, a new dynamic approach for context reasoning to solve waste management problem using IoTs and fog computing is proposed. The main goal of the proposed approach is to minimize the response time and energy consumption with optimal classification based on three Deep Learning (DL) models which are GoogleNet, ResNet and DenseNet.

The main contributions of this paper are:

- Proposing a dynamic reasoning model based on Fog computing for improving the performance of IoTs services.
- Minimizing the latency time and energy consumption for classification and processing based on cloud-fog model.
- Using and comparing three approaches of deep learning as a classifier for waste classification problem.

The paper is structured as follows: section 2 introduces some of relevant research done using Fog computing and DL. Section 3 formulates context reasoning problem for waste management in IoTs environments. Section 4 introduces the proposed reasoning model to solve waste management problem. Section 5 introduces the conducted simulation experiments and performance results of the proposed model. Finally section 6 gives the conclusion.

## 2. RELATED WORK

The main purpose of reasoning is gaining knowledge which does not exist in knowledge base. So, reasoning becomes significant in providing accurate and comprehensive context awareness. IoTs semantic technologies [9] enhance interoperability between IoT objects and it makes data access, knowledge extraction and semantic reasoning easier. Instead of being only in the cloud, Edge Computing (EC) is proposed to reduce dependency on the cloud and to balance workload of computing and data analytics and this achieves faster response. Semantic reasoning in the edge of IoTs is studied in [10] to measure the performance of reasoning in real IoTs environments. Five experiments were executed to find out the performance of reasoning and computing capabilities with deploying tasks in edge nodes. Authors in [11] proposed a multi model context aware reasoner with rules-based and Bayesian reasoning for three IoTs applications to deduce knowledge at the edge controller. Mobile Edge Computing (MEC) presented in [12] as an emerging technology that increases edge responsibility and allows storage, computation in real time, communication and control policy management to be hosted at the edge, which reduces network latency and bandwidth consumption, as it runs computing and storage capacities instead of sending them to the cloud.

Waste management is one of crucial applications of IoTs in smart cities. Different waste should be managed in a right way in order to avoid the side effects on the environment, health and ecosystem. Moreover, waste is passing through set of processes to minimize the growth of pollution and reduce the consumed cost and power by using recycling processes. In order to increase the recycled items, waste should be collected at earliest stage and classified with learning methods. In collection stage, IoTs notify collection by provided sensors to bins for measuring its status for emptied. IoTs is utilized to optimize waste process model [13] using smart bin including three layers which are data gathering, data processing and data demonstration layers. In this system, any user can access the system and upload many images at any time and this affects the system network. In addition, Ultrasonic sensors [14], [4] are attached to garbage collecting vehicles to send alerts to web applications through mobile network to demand the bin is ready to empty. However, ultrasonic sensors are prone to affect with temperature changes, humidity deviation consequently, sensing measurement and operation will be affected. The provided waste classification researches showed that there are several solutions for waste management using IoTs technologies. All approaches are similar approximately but different in IoTs technologies.

Recently, Machine Learning (ML) algorithms are used for waste classification to maximize the scale of recycled items. Deep learning methods are widely used for waste segregation which they are the optimal techniques to understand the image content. The main feature of DL methods is that it allows users to modify the method architecture by adding or removing layers to optimize the accuracy. Authors in [15] are used Support Vector Machine (SVM) and Convolution Neural Networks (CNN) for waste classification and the results showed SVM achieved high classification accuracy. In addition, Thung and Yang [16] deployed support vector machine (SVM) and a CNN to classify waste into six categories and the results achieved 63% for SVM and 23% for CNN. Moreover, waste can be classified into bio and non-biodegradable [17] using CNN in real time. However, CNN has stronger discrimination analysis, feature learning and it is suitable for large amount of waste, it consumes time in training. Training time depends on input images size, number of layers and Central Processing Unit CPU. Instead of building CNN form, modified CNN architectures are used for classification. ALexNet is a deep CNN architecture and it is also used to classify waste images in Multilayer Hybrid System (MHS) [18].In addition, authors in [19] compared two Dl models which are AlexNet and GoogleNet for waste identification and the results showed that, GoogleNet provided optimum results for waste classification and lower error rate. Another modified CNN architecture used to separate different components of waste is ResNet [21], it is one of an optimal methodology for the training of deeper Nets. It is used to classify waste into six groups and the results achieved 87\% accuracy. Moreover, authors in [22] used four CNN-based classification models (VGG-16, ResNet-50, MobileNet V2 and DenseNet-121) to separate waste into four classes.

## 3. CONTEXT REASONING PROBLEM (CRP)

In context reasoning phase for IoTs, the problem is how to minimize the latency time for sending and receiving data to the cloud. In addition, reduce the energy consumption and improve the IoTs services and processes. This problem is called Context Reasoning Problem (CRP). In this section, the assumptions and models are introduced then the CRP problem will be formulated.

### 3.1 System Model and Assumptions

Waste Management System life cycling includes, waste streams, waste collection, treatment and disposal methods, monitoring and regulation of the waste management process. For effective handling of these wastes like collection and disposal, IoTs concept is being used, which IoTs mainly deals with sensing, actuating, data gathering, storing and processing by connecting physical and virtual devices to the internet. Waste management objective is to minimize waste generation, reuse and increasing recycling rate to use it as a source of energy. The fruitful way for waste processing is classification by image processing. Classification in the cloud causes long latency because of physical distance. On the other hand, IoTs devices are unable to perform complex tasks because of limited computing and storage resources. Instead of being in the cloud, the idea of bringing computing and analytics closer to the end users/ devices has been recently proposed under the name of fog computing. Main fog benefits network latency and security risks. Hosting data fog nodes avoid transmitting large amount of raw data to distant cloud nodes. The main goal of this representation is satisfying all satisfaction requirements of reasoning processes that will be done in waste management problem to designate the optimal model for context reasoning based on optimal classification algorithm.

For a waste management problem in smart city, assume there is a set of sectors inside a city called $S=\{s_1, s_2, \ldots, s_m\}$, where each sector has a set of bins called $B=\{b_1, b_2, \ldots, b_l\}$. Every bin is used for measuring temperature, humidity and waste level by using sensors.

Assume that, bin requirement measures is represented by, $Req(b)=\{H, T, Wl\}$.

where H, T and Wl represent humidity, temperature and waste level, respectively.

Assume that there is a set of gathering nodes (fog nodes) FN, where $FN=\{fn_1, fn_2, \ldots, fn_j, \ldots, fn_p\}$ for every sector attached with a camera. Assume that each fog node in FN has a maximum energy and is denoted as $E_{max}(fn_j)$. This camera captures a set of waste images denoted as $G=\{g_1, g_2, \ldots, g_i, \ldots, g_k\}$. Assume that there is a set of class types denoted as $CI=\{c_1, c_2, c_3, \ldots, c_l, \ldots, c_h\}$. For example, CI can be the following six items CI= {cardboard, glass, metal, paper, plastic, trash}. Note that every image has to be classified as one of these items.

The classification energy consumption cost for every image $g_i$ on fog node $fn_j$ is denoted as $E(g_i, fn_j)$ and defined as:

$$E(g_i, fn_j) = Esen(g_i, fn_j) + Ec(g_i, fn_j) + ECRes(g_i, fn_j, cloud) \quad (1)$$

where

$Esen(g_i, fn_j)$: represents energy cost of sending image $g_i$ to edge node $fn_j$.

$Ec(g_i, fn_j)$: represents energy cost of classification image $g_i$ at edge node $fn_j$.

$ECRes(g_i; fn_j, cloud)$: represents energy cost of sending classification result for image $g_i$ to cloud layer.

The classification time cost for every image $g_i$ on fog node $fn_j$ is denoted as $T(g_i, fn_j)$ and defined as:

$$T(g_i, fn_j) = Tsen(g_i, fn_j) + Tc(g_i, fn_j) + TCRes(g_i, fn_j, cloud) \quad (2)$$

where

$Tsen(g_i, fn_j)$: represents delay time cost for sending image $g_i$ to edge node $fn_j$.

$Tc(g_i, fn_j)$: represents delay time cost for classification image $g_i$ to edge node $fn_j$.

$TCRes(g_i; fn_j, cloud)$: represents delay time cost for sending classification result for image $g_i$ to cloud layer.

The utility function for image classification can be defined as :

$$u(g_i, fn_j, c_l) = w_1 * \frac{1}{T(g_i, fn_j)} + w_2 * \frac{1}{E(g_i, fn_j)} + w_3 * \frac{1}{CF_{fn_j}(g_i, c_l)} \quad (3)$$

where:

$CF_{fnj}(g_i, c_l)$ : represents cost classification for image $g_i$ at edge node $fn_j$.

$w_1$, $w_2$, and $w_3$ are weights for time delay, energy consumption, and classification accuracy degree, respectively such that $w_1 + w_2 + w_3 = 1$.

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After getting the final decision, two operations will be done: (1) classification result (decision), $E(g_i, fn_j)$ , and $T(g_i, fn_j)$ will be sent to cloud layer to store it in the cloud storage devices and (2) classification result will be sent to end user.

### 3.2 Problem Formulation

The system model aimed to maximize the utility function provided that each image is classified as only one of result items. Based on system model and assumption the problem can be formulated as follows

$$Maximize\ \ U(G,N,Cl)=\sum_{i=1}^{k}\sum_{j=1}^{m}\sum_{l=1}^{h}u(g_i,fn_j,c_l)*x_{ij} \tag{4}$$

such that,

$$x_{ij}\in\{0,1\}\ , \tag{5}$$

$$\sum_{j:(i,j)} x_{ij}=1\ \ , \tag{6}$$

$$E(g_i,fn_j)\leq E_{\max}(fn_j)\ \forall\ fn_j\in FN, g_i\in G \tag{7}$$

Constraint (1) represents the decision variable $x_{ij}$, where if $x_{ij}$ is equal to 0, this means that an image $g_i$ for the edge node $fn_j$ is not classified by a class $c_l$ while if $x_{ij}$ is equal to 1, this means than an image $g_i$ for the edge node $fn_j$ is classified as an item of class $c_l$. Constraint (2) means that each image $g_i$ is classified as an item of class $c_l$. Constraint (3) means that the energy of classification image $g_i$ at edge node $fn_j$ is less than or equals the maximum energy of node $fn_j$.

## 4. THE PROPOSED ADAPTIVE REASONING APPROACH

In this section, to solve the Context Reasoning Problem, CRP, a new methodology called Deep Learning based Waste Classification Approach DLWCA is proposed.

### 4.1 Basic Idea

DLWCA approach is proposed to solve CRP problem for maximizing waste classification and minimizing time and energy consumption. To satisfy these goals the basic idea of DLWCA is based on: (1) using fog nodes for performing the classification process. (2) using deep learning methods in the classification process. (3) creating a real time decision alert mechanism for notifying end users. (4) building a layered architecture by using fog nodes with cloud server.

### 4.2 Proposed Model

Based on the basic idea, the proposed DLWCA is composed of four layers. (1) Sensing layer, (2) Fog layer, (3) cloud layer and (4) End user/control unit layer. The simulation workflow for DLWCA is shown in Figure 1. These layers are described as follows.

a. Sensing Layer: in this layer, DLWCA attaches camera $c_i$ for each dustbin $d_j$ to measure dustbin level humidity and temperature. In addition, dustbin details are sent to fog layer through network connection.
b. Fog layer: in this layer, DLWCA assigns fog node for each set of dustbins. This fog node will collect images from attached cameras and performs the deep learning classification process. In addition, it will send data and the classification decision to the cloud layer. Also, it use an alert system to send a notification to authority person if the dustbins are reached to threshold level. The main use for fog layer is to solve latency time problem for collection, classification and real time notification.
c. Cloud layer: in this layer, data is saved in cloud server as storage service for future analysis, big data processing, data visualization services and may be for merging the data with historical data to drive high level features. Moreover, analysis results and decisions are sent to end user/control unit layer.

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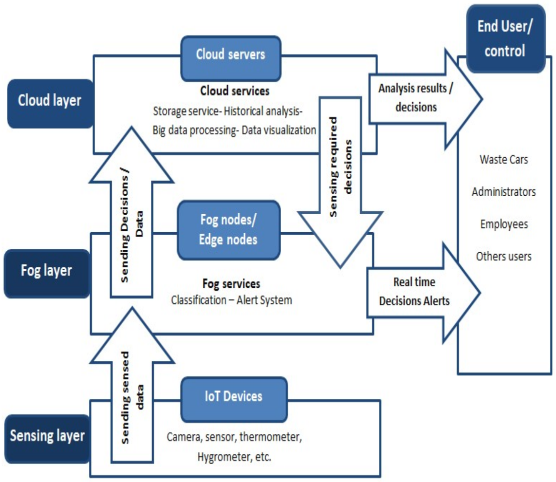


*Figure 1: System Workflow for DLWCA*

d. End user/ Control Unit layer: in this layer, final decisions for classification or collection are sent to automated waste cars or authority person or web application to implement the decision.

## 5. RESULTS AND DISCUSSION

Here, the results of conducted simulation of the proposed approach DLWCA will be introduced and discussed. The conducted simulations are based on: (1) cloud based classification, (2) fog based classification and (3) time and energy consumption for sending and receiving data (cloud -cloud/fog). The dataset used are collected through a set of cameras which represent the IoTs devices in the sensing layer in the proposed model in Figure 1. Moreover, the classification is done to classify solid waste to six items which are cardboard, glass, metal, paper, plastic and trash. The number of fog nodes is changed which is 5, 10, 15, 20, 25 and 30. DL methods are utilized for classifications which are GoogleNet, ResNet101 and DenseNet201 with freezing the initial 10 layers for the three models. Each experiment was conducted five times and the average of five times is calculated.

Here, the research problem is based on context reasoning for IoTs to solve waste management problem in terms of classification accuracy, consumption time and energy used. Context reasoning for IoTs means driving high level context based on the provided raw data. Deducing knowledge based on the knowledge base is commonly executed in the cloud layer. Cloud layer consumes high latency time and resource consumption. Instead of being only in the cloud, Fog layer is suggested as an intermediate layer to reduce the dependency of the cloud in terms of classification accuracy, latency time and energy consumption.

### 5.1 Classification Based Cloud

Figure 2 shows the results of classification accuracy against 765 solid waste items in cloud layer. It displays that GoogleNet accuracy varies from 72.5% for trash item to 89.7% for paper item. On the other hand, ResNet achieved higher accuracy 93.8% for cardboard item and 80%for trash item. DenseNet achieved higher accuracy equal 96.6% for paper item. The result indicates that the classification accuracy for DenseNet provides optimal accuracy comparing with GoogleNet and Resnet. This because GoogleNet reduces the feature space in the next layer and sometimes leads to lack of valuable input information and this affects the classification accuracy. In addition, every module for GoogleNet needs to be customized because of its heterogeneous topology. On the other hand, however, ResNet proposed deeper net for training and lower computational complexity, it explicitly preserves information through additive identity transformations due to which many layers contribute very little or no information [20].

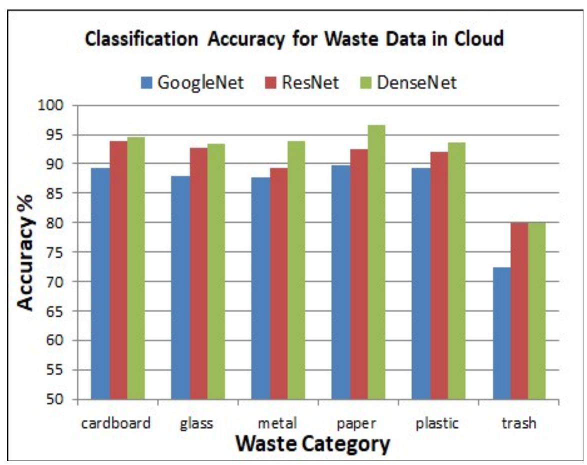


*Figure 2: Classification Accuracy Based Cloud*

### 5.2 Classification Based Fog

In the following experiments, different datasets with different sizes are used to measure the classification accuracy for waste items for cloud/fog layer.

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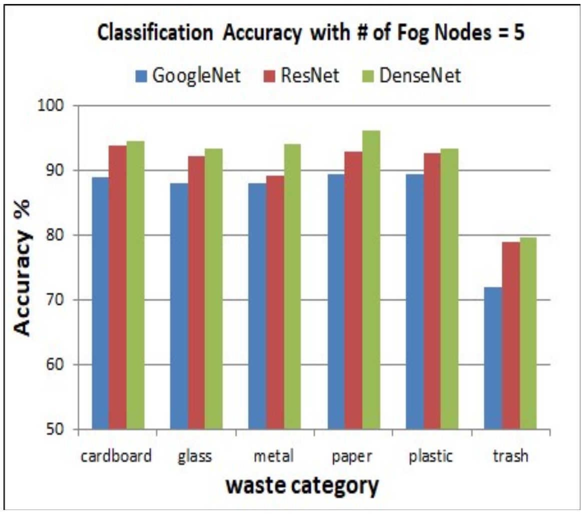


*Figure 3: Classification Accuracy Based Fog, Experiment 1*

Figure 3 shows the classification accuracy against solid waste items in cloud/fog layer when the number of fog nodes was 5 nodes. It shows that, GoogleNet achieved accuracy equal to 89.3% for paper and plastic items and 87.9% for glass and metal items. In addition, ResNet achieved higher accuracy for cardboard item equal to 93.8% in which the produced accuracy using DenseNet for cardboard is equal to 94.4%.

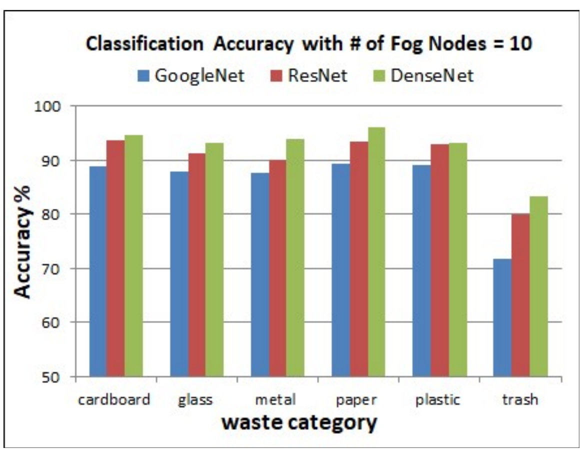


*Figure 4: Classification Accuracy Based Fog, Experiment 2*

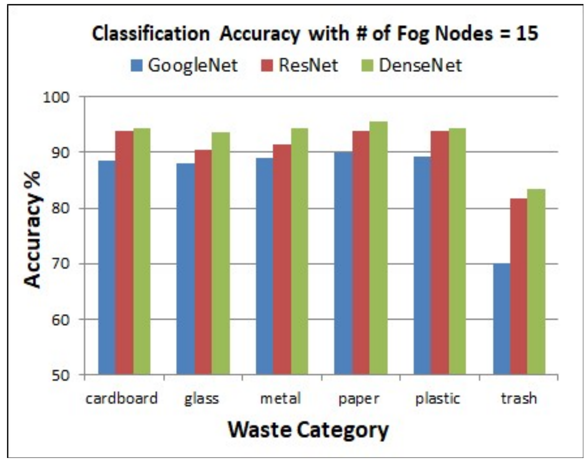


*Figure 5: Classification Accuracy Based Fog, Experiment 3*

Figure 4 shows the classification accuracy against solid waste items in cloud/fog layer when the number of fog nodes was 10 nodes. As shown in the figure, the classification accuracies for waste items using GoogleNet are approximately equal in which it achieved highest accuracy for paper item and it is equal to 89.3% while ResNet and DenseNet give accuracy of 93.3% and 96%, respectively.

Figure 5 shows the classification accuracy against solid waste items in cloud/fog layer when the number of fog nodes was 15 nodes. As can be seen in the figure, for trash item, GoogleNet does not perform well in which it achieves only 69.9% for trash item. On the other hand ResNet and DenseNet produce good results for trash item where ResNet has 81.6% accuracy and DenseNet gives accuracy of 83.4%. In addition paper item achieved highest accuracy equal to 90%, 93.7% and 95.6% for GoogleNet, ResNet and DenseNet, respectively.

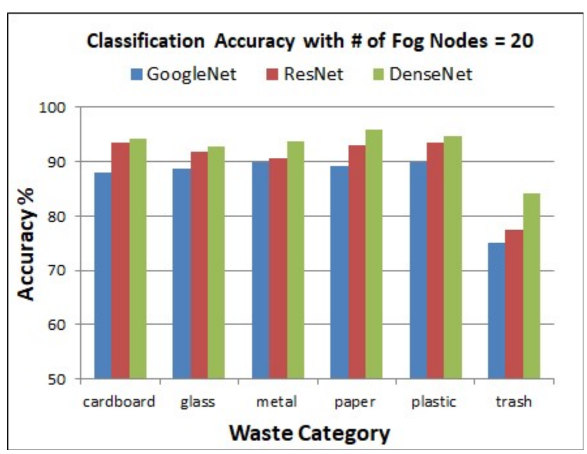

*Figure 6: Classification Accuracy Based Fog, Experiment 4*

Figure 6 shows the classification accuracy against solid waste items in cloud/fog layer when the number of fog nodes was 20 nodes. As shown in the figure, for GoogleNet, the classification accuracies for cardboard, glass, metal, paper and plastic items are approximately equal and they varies form 88% to 89.8% while the trash item achieved only 75.1% accuracy. For ResNet, the accuracy is varied form 90.5% to 93.6% for the first five items while the trash item achieved only 77.5%. However, the best accuracy is provided by DenseNet in which it achieves the peak accuracy for paper item equal to 95.5% and the trash item produces 84.2% accuracy.

Figure 7 shows the classification accuracy against solid waste items in cloud/ fog layer when the number of fog nodes was 25 nodes. It displays that, the classification accuracies for waste items using GoogleNet are approximately equal in which it achieved highest accuracy for plastic item and it is equal to 89.7% while the accuracy using ResNet is equal to 93.1%. On the other hand, DenseNet produces peak accuracy for paper item equal to 95.9% and lowest accuracy for trash item equal to 82.8%.

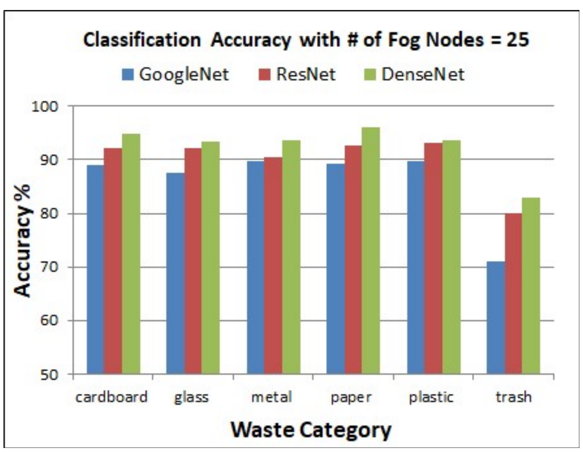


*Figure 7: Classification Accuracy Based Fog, Experiment 4*

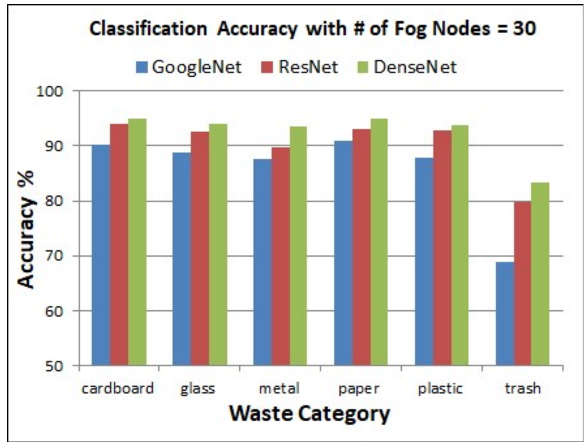


*Figure 8: Classification Accuracy Based Fog, Experiment 4*

Figure 8 shows the classification accuracy against solid waste items in cloud/ fog layer when the number of fog nodes was 30 nodes. As shown in the figure, for trash item, GoogleNet does not perform well in which it achieves only 86.8% while ResNet and DenseNet produce accuracy equal to 79.6% and 83.3% respectively. On the other hand, GoogleNet method achieves highest accuracy equal to 90.8% for paper item while ResNet and DenseNet produce higher accuracy for cardboard item equal to 94.1% and 94.9%, respectively.

Figure 9 shows the average classification accuracies of GoogleNet, ResNet and DenseNet against cloud node CC only without any fog node and different values of fog nodes which are denoted as $CF_5$, $CF_{10}$, $CF_{15}$, $CF_{20}$, $CF_{25}$, and $CF_{30}$ when the number of fog nodes were 5, 10, 15, 20, 25, and 30, respectively. As can be seen in the figure, for cloud layer, the classification accuracy for GoogleNet, ResNet and DenseNet are equal to 88%, 91.5% and 93.7%, respectively. For cloud/fog layer, the classification results are approximately equal in which it is about 87%, 91% and 93% for GoogleNet, ResNet and DenseNet, respectively. This means, the classification results for cloud and cloud/fog layer are almost the same but in the same time, latency time and energy consumption that are achieved by cloud/fog layer much lower than that are achieved by cloud layer. In addition, the used DL models improved the accuracy compared to other researchers using the same dataset [21].

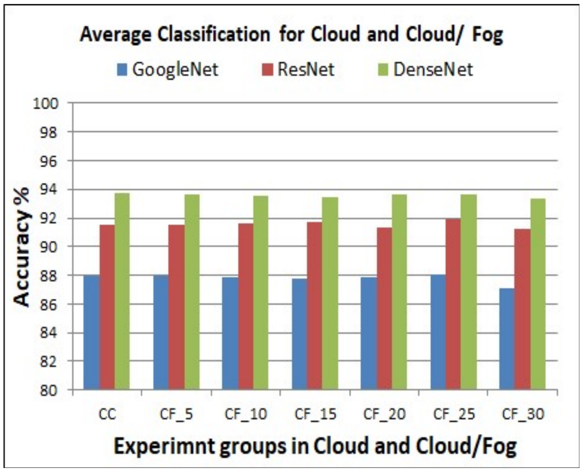


*Figure 9: Classification Accuracy of Cloud and Cloud/ Fog*

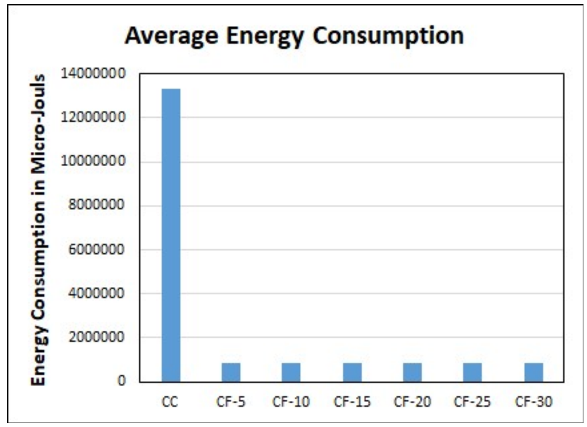


*Figure 11: Average Energy Consumption for Cloud and Cloud/ Fog*

### 5.3 Time and Energy Consumption

In the following experiments, averages of execution time, energy consumption, time delay and network usage for cloud and cloud/ fog layers are measured and compared.

Figure 10 shows the execution time in MSeconds against different values of fog nodes $CF_5$, $CF_{10}$, $CF_{15}$, $CF_{20}$, $CF_{25}$, and $CF_{30}$. As shown in the figure, the execution time in the cloud layer is about 445 ms. On the other hand, the execution time in cloud/ fog layer is started with 396 ms with 5 experiments and it climbed gradually with increasing the number of experiments until it reaches to 440 ms for 30 experiments. This means, the execution time in cloud/fog layer rises with increasing the number of fog nodes. In addition, the reduction ratio for execution time was between 2% and 10% less than values by using cloud layer only.


*Figure 10: Average Execution Time for Cloud and Cloud/ Fog*

Figure 11 shows the energy consumption in Micro-Jouls against cloud node $CC$ and different values of fog nodes $CF_5$, $CF_{10}$, $CF_{15}$, $CF_{20}$, $CF_{25}$, and $CF_{30}$. It can be noticed that, the energy consumed in the cloud layer is much higher than energy consumed in cloud/ fog layer. This is because; the consumed energy in the cloud concludes sending data to cloud for classification, storing result and sending the result to the end user. In addition, the reduction ratio for energy consumption was 94% less than values by using cloud layer only.

Figure 12 shows the time delay in MSeconds against different values of fog nodes $CF_5$, $CF_{10}$, $CF_{15}$, $CF_{20}$, $CF_{25}$, and $CF_{30}$. As can be seen in the figure, the latency time in cloud layer is about 114.7 ms and it is higher than time delay in cloud/fog layer. In addition, as can be seen, the time delay for cloud/fog layer increases with increasing the number of fog nodes. This means, an additional time is needed for more fog nodes. In addition, the reduction ratio for time delay was 4% less than values by using cloud layer only.

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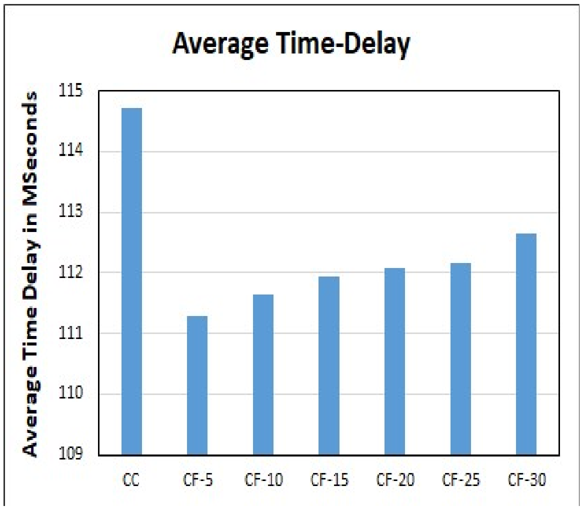


*Figure 12: Average Time Delay for Cloud and Cloud/ Fog*

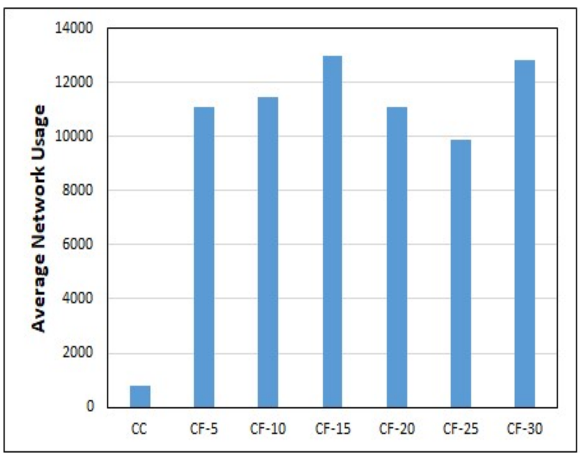


*Figure 13: Average Network Usage for Cloud and Cloud/ Fog*

Figure 13 shows the network usage against cloud node CC and different values of fog nodes $CF_5$, $CF_{10}$, $CF_{15}$, $CF_{20}$, $CF_{25}$, and $CF_{30}$. It shows that, the network used for classification in the cloud layer is much lower than the network used for cloud/fog layer. In addition, the reduction ratio for network usage was 92% greater than values by using cloud layer only which indicates the use of network resources with a high degree of efficiency.

Based on simulation results, the major findings of the proposed DLWCA are: (1) the conducted classification results for cloud and cloud/fog are almost the same, (2) the energy consumption for cloud layer is much higher than fog layer, (3) the network usage for cloud layer is much lower than cloud/fog layer and (4) the execution time is approximately rises with increasing the number of fog nodes.

## 6 CONCLUSION

In this paper, a context reasoning problem in context management systems for IoTs is described and introduced. To solve this problem, a new dynamic approach is proposed called Deep Learning based Waste Classification Approach, DLWCA. DLWCA uses fog nodes and deep learning methods to improve performance of waste management using IoTs and meet its challenges which are real time actions and limited resources of IoTs devices as battery, bandwidth and storage. The conducted simulations results show that the performance of waste management in terms of execution time, energy consumption, and sensor time delay is improved by using fog/cloud layer comparing with cloud layer. Also, classification process is improved using deep learning methods which it defines useful features for every raw data to make a decision. The conducted classification results for cloud and cloud/fog are almost the same however; energy consumption and time delay is reduced in cloud/fog layer. In future work, the proposed DLWCA will be studied with real IoTs scenarios. In addition, using more deep learning methods for classification will be considered.

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