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HARNESSING IoT AND DEEP LEARNING FOR SUSTAINABLE WASTE REUSE IN CEMENT FACTORIES

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ABSTRACT

In this research paper, the innovative application of Deep Learning (DL), especially deep neural network algorithm, is explored to improve the waste management and recycling strategy in cement factories. As important as the cement industry is in building cities, its production is a major contributor to environmental pollution. Large amounts of gaseous waste, slag and kiln dust negatively affect human health and the environment. Traditional waste management strategies lack efficiency and sustainability, which leads to waste of resources and increased landfills. This study aims to build an effective strategy for recycling and improving by-products using an Artificial Intelligence (AI) algorithm for smart management to preserve the environment and predict the best way to work in cement factories. Controlling the feedback weight of neural network derived from the data comes from the Internet of Things (IoT) as the sensors play the key role in enhancing the results. The study showed through the results that SVM was able to identify the best path for optimal waste reuse and dispose of 30% of waste in recycling. The results proved in terms of reducing CO2 emissions and reducing RMSE on historical data and achieved the accuracy of 95% that improved the strategy. This study sheds light on the possibility of using artificial intelligence algorithms as tools to drive sustainability in the industry, especially the cement industry, and the future research avenues in this direction.

Keywords: *Cement Factory, Deep Learning, Internet of Things, Neural Network, Environment.*

1. INTRODUCTION

The cement industry is one of the most important sources of global carbon dioxide emissions, accounting for 8% of global emissions. In addition, it generates a lot of waste such as kiln dust, slag and heat. Traditional waste management fails in this area of reuse. This leads to inefficiency in terms of the environment and economy. Emerging technologies such as the Internet of Things and deep learning help in modern solutions and challenges in this area. In the Internet of Things, it contributes to monitoring and taking measurements that are difficult to adopt in traditional technologies, and in order to work in real time. On the other hand, deep learning works on powerful analyses to reach decision-making. The integration of Internet of Things and deep learning technology can revolutionize waste management in cement factories and for sustainability. As shown in Figure 1.

Figure 1: Cement Factory with proposed IoT

Urban development and industry in most societies have led to environmental pollution and thus global warming [1-2]. Cement plays a major role in the modern world [3]. In many developed countries, cement uses are increasing, especially in construction [4-5], engineering arts [6-7], and the medical field [8]. There are many economic benefits of cement through job creation and improving industry [9-10]. Therefore, the cement industry suffers from difficulties due to sustainability and polluting waste. Despite its contribution to building the economy [11-12]. Cement is considered one of the basic and important components in industry in the world, so global production reaches the

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production of concrete (1 ton) per person annually [13-14]. In 2021, global cement production is estimated at 3,600 million metric tons [15-16]. According to forecasts, as shown in the figure, world cement consumption may reach 5,800 million metric tons in 2050. As shown in Figure 2.

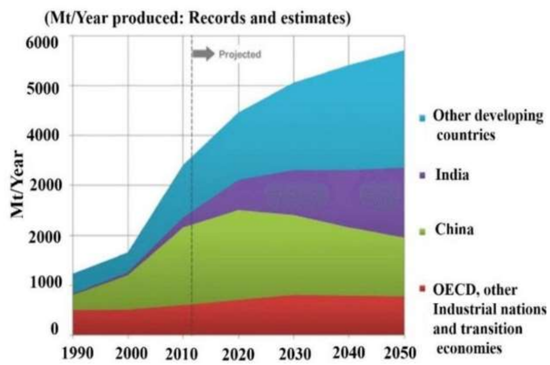

Figure 2: consumption of Cement estimates around the world [17]

Due to this increase in cement production, awareness of the negative impacts on the environment has increased in societies and due to its availability in the global market [18]. Cement factories contribute to increasing atmospheric pollution due to the gases they release. Increased production, fuel used, and dust control contribute to the concentration of pollutants [19]. Many global studies and reports have confirmed that the source of particle emissions is cement production and represents 40% of total factory pollutants [20]. The types of emissions resulting from cement production factories are nitrogen oxides NOx and particulate matter PM as well as sulfur dioxide SO2 [21]. As a result of the increase in infrastructure, especially those related to cement and concrete, it deteriorates due to the release of carbon dioxide CO2. Pollutants are produced in the cement production sector in several ways, including handling raw materials, kiln processing, grinding final cement, crushing lime, clinker production and storage, and power generators. Complaints from residents near cement factories about polluted dust and the thick layer of pollutants have increased, and many residents in nearby areas are unaware of the seriousness of the pollution, which does not only affect humans but also plants and the aquatic environment [22].

Cement production is a very important industry that is fundamental to supporting infrastructure at the urban level. However, it is considered one of the most resource-intensive and environmentally impacting processes. It is known that cement production requires large amounts of raw materials, energy and water, which in turn generates a lot of waste. These wastes include cement kiln dust (CKD), unused clinker, particulate matter and many solid particles that affect the environment if not managed properly. Cement factories contribute to industrial carbon dioxide emissions, which have a negative impact on the climate. There are significant challenges facing the industry today, including the cement industry and the sustainable management of industrial waste products. As in the case of cement dust resulting from kilns, which is a fine powder from the heating process waste and contains unreacted raw materials such as fuel ash. Improper disposal of this dust leads to health effects for the nearby community through air pollution and soil pollution. These fine particles left over from grinding significantly pollute the air, and improper handling of some solid waste can overburden landfills [23].

Waste management is one of the innovative solutions that came in response to the development and growth of sustainable environment and societal pressures to make the environment green. One of the promising technologies in management is Deep Learning techniques and is used for waste management here to enhance the efficiency of sustainability and obtain strategies that facilitate the reuse of waste. DL is part of artificial intelligence algorithms that are characterized by accuracy and correct prediction when analyzing big data and by identifying patterns, decisions are made that contribute to improving the cement industry in real time. Through the features of artificial intelligence and its predictive ability to make strategies intelligently, waste can be reused effectively, which contributes to environmental safety and thus the circular economy [24].

In cement plants, there are many opportunities for improved waste management strategies by integrating Deep Learning. Deep Learning algorithms can obtain information from sensors to help predict the composition and use of cement kiln dust, leading to improved recycling methods for building materials such as tiles and concrete. Artificial intelligence (AI) algorithms can determine the optimal use of cement dust in soil stabilization as an acid neutralizer or as an admixture in road construction. ML applications can control heat and recover heat from exhaust gases produced during production, and by controlling heat and reducing waste in it, it helps promote clean environments and reduce carbon pollution. Machine learning can control work and not release polluting particles that increase during production, thus controlling the work environment, reducing waste, increasing

cement productivity, and keeping emissions within regulatory limits [25].
This study aims to highlight the role of DL in reusing waste in cement factories to achieve sustainability. By applying DL to all stages of production to achieve good waste management by predicting wasted materials to help in reuse. This study focuses on the potential of artificial intelligence algorithms to revolutionize waste management in industry in general and the cement industry in particular. The study focuses on specific wastes in the cement industry such as cement kiln dust flows, thermal emissions and particulate matter and how they can be converted into valuable resources as by-products. Thus, this study contributes to studies in the same field to enhance technologies that work on artificial intelligence to manage data that will transform industrial facilities to be more efficient and environmentally friendly. Implementing AI-based strategies is not only able to reduce the environmental impact of the cement industry, but it is also able to create opportunities for industrial and economic growth through innovative reuse processes. This contributes to the concept of a circular economy, which means using waste as a resource on an ongoing basis.

1.1 Cement Production

Cement consists of a set of raw materials such as clay, limestone, sand and rock clay. The materials go through several stages such as crushing, grinding and others as shown in Figure 3 [26]. The production steps are important to know in order to understand the system and evaluate the work. They are initially divided into four main stages:

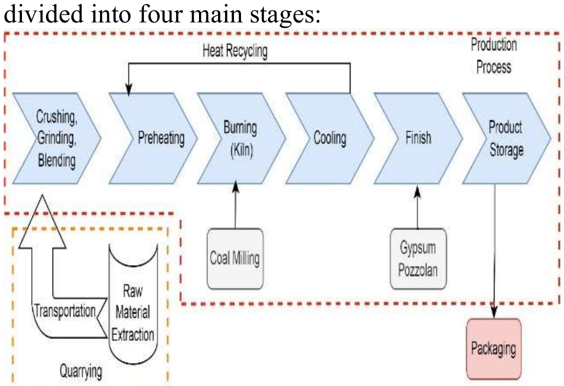

Figure 3: cement production stages

Quarrying Process

The clay stone is extracted by blasting and then the silica is extracted by crushing. The materials are transported to the crushing and grinding device in two stages by conveyors. They are transported by belts to the factory.

Preparation process

This stage includes mixing and grinding the raw materials that were previously extracted in order to obtain a suitable chemical mixture. It basically consists of several secondary stages:

- *Grinding raw materials*

The materials are mixed at this stage using hot air at 290°C and centrifugal motion and are smoothed and ground by balls. The mixture is then filtered and homogenized in a silo and the grinding process is repeated for the course materials remaining from the process. Homogenization is an important process here to achieve the desired composition and is a sign of the quality of the mixture. The operation of the kiln can be controlled if homogeneity is not complete.

- *Preparing fuel*

At this stage the coal is ground as in the raw milling process, after which the finely ground coal is conveyed and hot air is injected to dry it through the burner.

- *Burning in kiln*

This stage is considered the major heating stage where the mixture is heated to 500 degrees Celsius, after which it is transferred to be mixed with dust and static gas at a lower temperature of 330 degrees Celsius, and then the temperature is reduced to less than (120) degrees Celsius. Heating helps to isolate the microelectrodes and particles that are in the gas. The mixture of (CaO) and (MgO) goes through several processes at the beginning, its temperature is raised to 1450 degrees Celsius, from which (CO_2) gas is emitted, and then it is cooled by spraying water.

- *The grinding cement mill*

In this process, the clinker is kept at 125 °C to prevent all blockages by dry or wet materials of the cement equipment. This occurs when dust accumulates in the walls, and then the gypsum and clinker are processed in the mill in two grinding stages and in two different chambers. Then the cement is transferred to the separation stage and the fine cement is transferred to the silo, while the rest of the raw materials are returned to grinding.
After the main operations, conveyors are used to transport the product to storage silos and then to external transport to the consumer. The weight of one bag is usually 50 kg, which is the basis for making concrete and construction [27]. Two processes accompany the dry and wet cement industry. The dry process is the process of drying the product with hot air during or after grinding, and the

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wet process is the process of adding water to the product to avoid sticking.

1.2 Pollution Generated by Cement Factory

Pollutants are released at all stages of cement production and are considered a threat to human health. Pollution to which humans are exposed is either directly through air inhalation or indirectly through soil and water pollution. According to studies and reports, pollution often affects the respiratory, lymphatic, digestive and central nervous systems [27], as shown in Figure 4, which shows the effect of cement factory pollution.

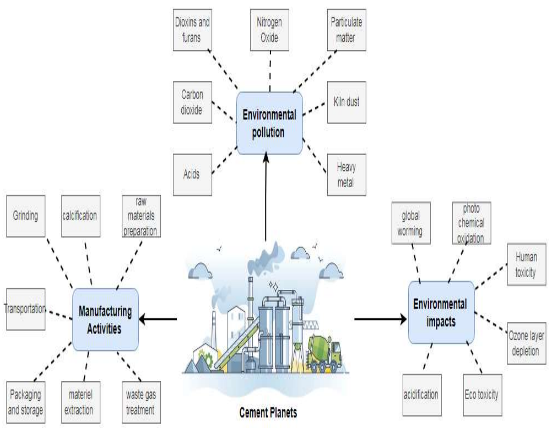

Figure 4: Pollution from cement factory

Five major categories of pollutants are emitted by cement plants: air emissions, solid waste, waste fuel itself, waste water pollution, and noise pollution [28].

1.3 Internet of Things (IoT)

The cement industry is the cornerstone of the world’s urban infrastructure, producing approximately 4 billion tons of cement per year. However, it is also a major contributor to environmental pollution. The large amounts of waste it generates, such as kiln dust, slag, heat and carbon emissions, are uncontrolled and must be monitored and controlled.

Emerging technologies such as the Internet of Things (IoT) offer the potential to address these challenges. Sensors monitor the production process remotely and control it automatically in real time by connecting them to end devices. IoT provides valuable data on pollutant and waste flows and energy usage. This data provides an efficient working environment when combined with deep learning technology. Thus, analyzing patterns, predicting waste behavior and suggesting optimal recycling.

For smarter waste management, IoT is being integrated with deep learning in cement plants for very good management. This approach enhances operational efficiency, sustainability and waste reduction. This research presents a good approach to revolutionize waste management in cement plants and enhance the environment and economy.

1.4 Deep Learning

DL is one of the most important applications of AI that we will take into consideration in this study. To review the applications of DL in waste management, it is first necessary to understand the basic concepts related to this field. Below we present some basic principles and definitions. Artificial intelligence techniques are used in many applications such as military, industrial, security, etc. [29-31] AI techniques have helped in analyzing data obtained from waste in factory, which is often necessary and has a large economic dimension.

DL is an application of artificial intelligence that enables systems to learn on their own and improve their performance through experience and expertise without the need for specific programming. This field focuses on developing computer programs that can access and use data in the learning process [32]. This process begins with observations or data, such as practical examples, direct experiences, or instructions, where this data is used to discover patterns and make more effective decisions based on the examples provided. The main goal of machine learning is to enable machines to learn independently without human intervention, and to adapt their actions according to the results they reach.

DL is considered a part of artificial intelligence, which is considered a main title, and in turn it consists of a smaller part that contains it, which is deep learning, as in Figure 5. For each application, artificial intelligence algorithms work to solve it, and one of them can work efficiently and another may not work with the same efficiency.

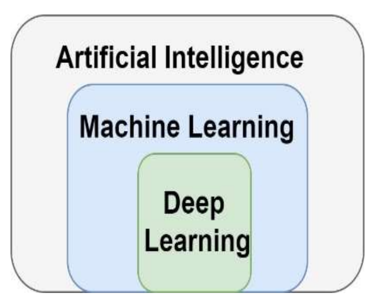

Figure 5: Relation among AI, ML and DL

DL allows for the analysis of large amounts of data, and typically provides faster and more accurate results for identifying profitable opportunities or high risks. However, DL can require additional time and resources to ensure it is properly trained. DL relies on curated data that is used to analyze and build the learning model, which means the need for a suitable set of data that can be used effectively in the learning process.

Many DL algorithms suggested in literature, and choosing the most suitable algorithm for a particular problem depends on a set of characteristics such as speed, accuracy, training time, prediction time, amount of data required for training, type of data, ease of implementation, etc. Often, the time factor is of utmost importance, especially in waste manegement.as shown in Table 1 [33].

Table 1: Time complexity of some AI algorithms

Algorithm	Learning	Predicting
Regression	O(p2n+p3)	O(p)
Decision Tree	O(n2p)	O(p)
Random Forest	O(n2pnt)	O(pnt)
Naïve Bayes	O(np)	O(p)
SVM	O(n2p+n3)	O(pnsv)
KNN	---	O(np)
K-means	O(npk+1)	O(k)

For avoiding dependency on certain condition, have to analyze algorithm runtime for asymptotic sense. Thus, n represent training number, and p is feature number, while *nt* is the tree number and *nsv* support vector number, *k* represent the cluster number. And the complexity of ML is calculated according the table.

Learning time is the time required to train the model using the dataset, and depends on the size of the data and the type of algorithm used.

Prediction time is the time required to test the model using a new dataset or predict unseen data, and also varies depending on the size of the data and the type of algorithm used.

In most cases, about 80% of the dataset is allocated for training, while the rest is used for fine-tuning and testing. It is worth noting that the training phase is often performed offline, which makes prediction time even more important for developers.

In general, the above criteria can be used to select a number of suitable algorithms, but it is difficult to determine the best algorithm at the beginning. Therefore, it is preferable to follow an iterative approach to work. A set of potential algorithms can be selected from among the machine learning algorithms, and tested on the data by running them in parallel or serially, and then their performance is evaluated to select the most effective algorithm.

In the following section, the proposed method will explain the reason for using the SVM classifier and how to enter information from GIS into the classifier in order to analyze it and find the best ways to achieve smart city.

1.5 Waste of Cement Factory within AI

Artificial intelligence is a technology that has recently gained popularity and has advanced very rapidly in all areas of life. Especially in waste management and reducing its harms [34]. In order to increase sustainability and operational efficiency, artificial intelligence and robotics technology are being integrated into waste treatment and management plants. This integration can revolutionize this sector. Many developed countries such as the United States, Canada, Singapore, and others have relied on artificial intelligence technology in the use and recycling of resources and reducing the impact of solid waste [35]. Gaseous or solid waste management has become widespread and very important at the present time. From this standpoint, artificial intelligence has become very important in sustainable waste management, especially in cases of a circular economy free of waste and taking into account the economic, environmental and social conditions. The importance of artificial intelligence in waste management in smart cities is highlighted by recycling waste for environmental safety Studies have relied on reports on the costs of waste from landfilling, dumping and transportation and comparing them with recycling and increasing the sustainable environment, and they found that recycling is much better from an economic and health perspective [36]. Studies have emphasized the need to find a new management thinking to move to a circular economy free of waste [37]. Figure 6 shows the basic concepts of using artificial intelligence in waste management and sustainability.

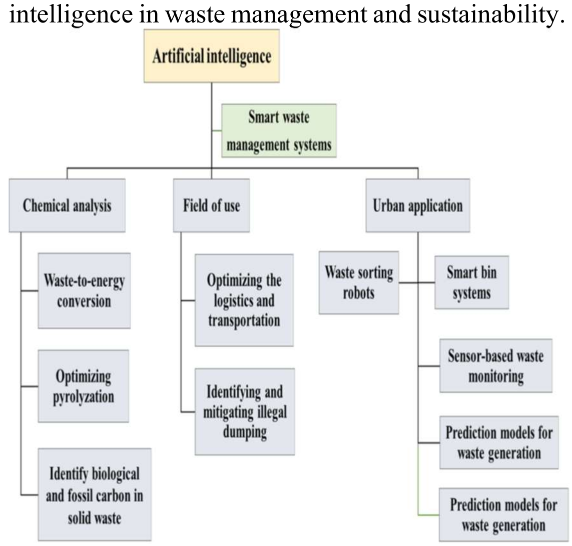

Figure 6: using AI in management of waste [38]

2. RELATED WORK

In cement manufacturing, waste is used as a supplementary or alternative fuel to raw materials, and in both cases it provides a good option for waste reduction and energy conservation at the same time [39]. Co-treatment of problematic waste has been used for many types of waste such as sanitary landfill, organic waste, contaminated soil and ash [40]. In Europe, waste from cement plants with high calorific values and waste-based raw materials are used as primary fuels according to the Stockholm Convention [41] and the Basel Convention, which includes technical guidelines and basic principles for the use of industrial waste [42]. Cement kilns are widely used in the world to incinerate waste. This experience has been gained by developing and emerging countries over the past few years [43]. Emerging countries, including China, use cement kilns to treat waste such as landfill sludge as well as hazardous waste such as some persistent organic pollutants [44] and wastes that are hazardous to humans such as fly ash. In developing countries, co-incineration in cement kilns for waste disposal is increasing significantly. Countries such as Germany and Switzerland have more than 40 years of experience in using raw materials and waste-based fuels since the 1970s [45] and the proportion of waste-based fuels in Germany was 67.5%, while in Switzerland [46] it was 65.5%. Their experiences in emission control and waste management have been of interest to developing countries in controlling and burning co-fuels in cement kilns. The European Union regulated waste incineration in 2000, and this directive covers all EU countries. However, some countries, such as Germany, have enacted more comprehensive and stringent individual regulations on waste incineration before joining the EU [47], so Germany is currently a leader in this area in the cement industry. [48] Used deep learning, to calculate the concentrations of heavy metals that enter into the cement industry, such as chromium, arsenic, cadmium, and mercury, and build a model to plot the concentrations and predict acceptable levels. [49] Used Deep Neural Network to model the calcination stage of cement to control CO2 output, predict and control emission rates. In a study, the benefits of the Internet of Things in security challenges in cement plants, and maintaining safety in avoiding risks due to actual response [50]. A multi-agent system (MAS) was used for distributed control of the Internet of Things and the development of communication between sensors and cement plants, in a real study that transmitted data over the Internet for remote control [51].

Many studies suggested in the literature consider IoT and an AI algorithm to control the waste of cement factories and keep the environment clean. The following section will illustrate the proposed method in detail.

3. METHOD

Many efforts are being made to automate factories and plants and to protect the environment from their waste. Cement factories are among the most polluting products in the environment. To control these wastes, we propose sensors in waste production sites to read the information and thus process and analyze the information and automate the work in the factory. The method used consists of several stages, starting with collecting information from a standard dataset and preprocessing the data, then extracting the important features and storing them in special vectors, as shown in the Figure 7.

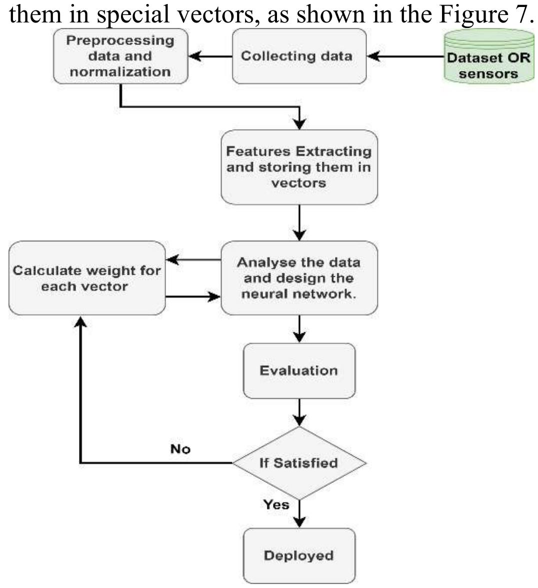

Figure 7: General framework for proposed method

When extracting features, a neural network is designed based on the weights of the features to enter the data in the vectors to the input layer in the neural network and then the hidden layers to produce the result after implementation in the output layer. In the event that the result is not obtained, the design of the hidden layers is changed based on the feedback data, and calculated and classified to contribute to building the neural network in the next cycle. As in Figure 8.

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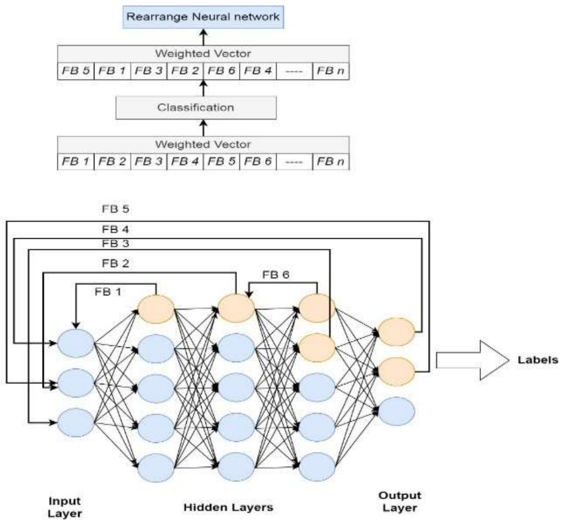

Figure 8: Design neural network

Restructuring the neural network during iteration and based on intermediate variables produces the best result and a state of complexity to reach the best result. The work of deep learning here comes from repeating iterations that change the state of the result in each iteration that takes place during the training process. In this process, the intermediate outputs (feedback) have an impact on the result each time. The ideal result can be obtained through repetitions on the same data and on other data in the dataset. Deep learning design can be made by repeat the neural network with other data through training mode. As illustrated in Figure 9.

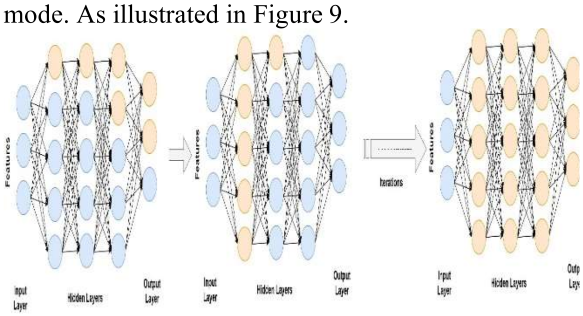

Figure 9: construction on DL

First, we define IoT data as inputs and a deep learning model to predict the pest state for the contamination.

To represent the input such as $x = \{x_1, x_2, \ldots, x_T\}$ as sequence where x_i consider as vector for feature extracted from data or sensors at time i, then the T represent the total length of the sequence.

Deep learning model can be represent as $f(x;\theta)$ of parameter θ such as :

$f(x;\theta)$ Consider the output of model, with the probability distribution to the predefined action. Multiple layers included in the system like encoder (to input sequence) and decoder (to output action). Can represent the output as :

$$y = f(x; \theta) \qquad (1)$$

Next step have to train the model by using the loss function which measure the discrepancy between the predicted results and the actual results taken (ground truth). Common loss function can find by:

$$L(\theta) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C} y_{i,j}\log(\hat{y}_{i,j}) \qquad (2)$$

Such as: N consider the total number of training from dataset,

C consider number of results,

$y_{i,j}$ Consider the label of ground truth for *j-th* predicted and *i-th* example,

$\hat{y}_{i,j}$ Represent the prediction with probability of *i-th* example and *j-th* action given by model$f(x;\theta)$.

In the next section, the Results section, we will explain how the DL with IoT and their accuracy relate to the concentrations of raw materials that cement factories deal with.

4. RESULT AND DISCUSSION

Sensors were used to detect features that show correlations with variables related to increased CO2 generation. Data from approximately 5,000 historical samples from the dataset containing labels were used. In the cement plant outputs there are sensors to collect readings for feedback and instantaneous pollutant levels. The algorithm works along the production line starting from material preparation and mixing ratios in raw materials to the total packaging before transportation. Data is collected during the work phase, analyzed and compared with the outputs (waste) in order to control the production process. As shown in Figure 10.

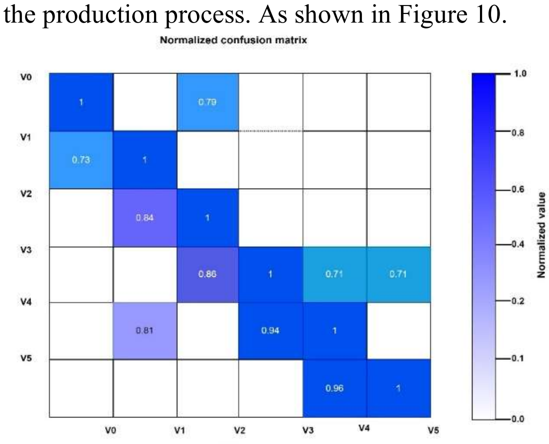

Figure 10: Correlation of heat map and prediction of CO2

An important criterion in this regard is the Root Mean Squared Error (RMSE), or root mean square deviation. It is used to evaluate the accuracy of forecasts, and separates forecasts from actual values. The RMSE ratio varies from one algorithm to another to express the best algorithm followed, here using the Deep Learning gives better accuracy than other algorithms, which indicates the closeness of the data and its slope within the distribution and is measured as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \qquad (3)$$

Such as N represent the number of entered data for each iteration, y_i represent the actual data and $\hat{y}_i$ is predicted value. The outputs of the cement plant are evaluated and waste pollution measurements are made, depending on the error rate between the actual and expected data and over a period of time. A graph summarizing the feasibility of the proposed algorithm can be shown as in the Figure 11.

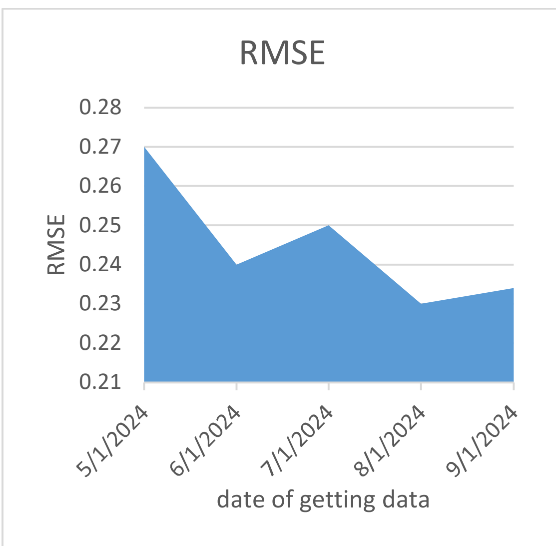

Figure 11: RMSE of the proposed system within period of time

The study confirmed that little carbon monoxide is produced from the raw materials of cement factories. The concentrations of the raw material mixtures used in it are 600 mg / m^3, and represent the average values of carbon monoxide production in Iraq for the past years, which have greatly exceeded this value. This represents government factories, while private factories also contribute, but there is no real data on them. Most of the pollutants come from primary or secondary combustion during the processing stage in cement factories, as shown in the Figure 12.

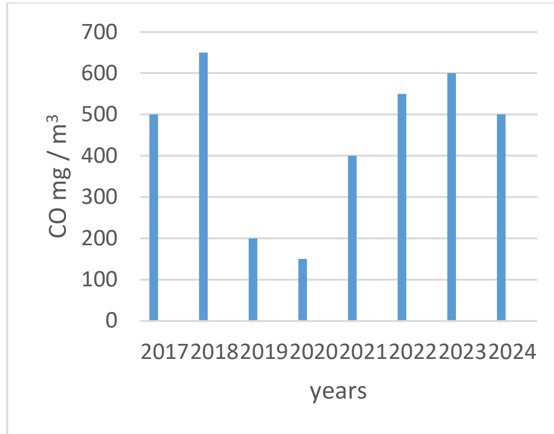

Figure 102: production of CO in cement factory eight years

Accuracy is one of the important criteria that we rely on when implementing a deep learning algorithm in the industrial field, especially cement factories. It is the model's ability to classify and correctly predict outcomes (for example, waste management and reuse strategies). Figure 13 shows the improvement in accuracy for the deep learning model over 20 epochs, which shows the strength of the model in obtaining correct predictions.

The accuracy for classification can be find by:

$$\mathrm{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total predictions}} \times 100 \qquad (4)$$

According to N samples from dataset we can compute y_i (True label of i-th sample) and $\hat{y}_i$ (predicted label). Then the model of accuracy through dataset given by:

$$\mathrm{Accuracy} = \frac{\sum_{i=1}^{N} 1(\hat{y}_i = y_i)}{N} \qquad (5)$$

Consider 1(.) refer to true prediction and 0(.) otherwise.

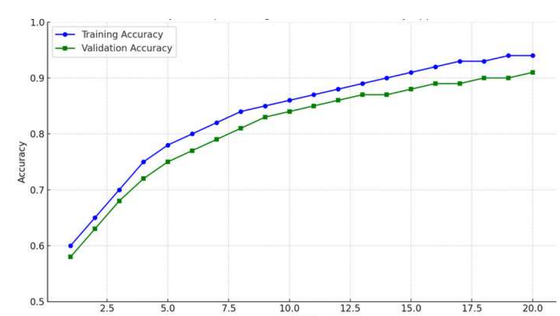

Figure 113: Accuracy during training mode

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5. CONCLUSION

In this study, deep learning represented by the feedback control of neural network was integrated to assist in waste management from cement factories, which plays a role in waste reuse as a waste recycling strategy. Many wastes are produced from cement factories, including gases, suspended solids, and heavy materials that negatively affect humans and the environment in all its aspects, such as air, water, and soil. The wastes considered in this study, such as slag, flying dust, and kiln ash, can be used in waste management to reduce pollution by 30% and contribute to the production of environmentally friendly materials. This study enhances the industry and its commitment to sustainability through the results obtained in RMSE = 0.25% and training on historical data of carbon monoxide and carbon dioxide emissions. DL contributed to improving the strategy for recycling waste emitted from cement

6. FUTURE WORK

There are many promising future directions for the use of deep learning algorithms, especially based in the weight of feedback, in waste management for cement plants. The deep learning model can be generalized to include all wastes and more diverse in cement plants. Hybrid deep learning can be used to create a new strategy for waste management and recycling. The ability to predict and adapt can be enhanced by using other artificial intelligence algorithms such as RNN, decision trees, etc. The work can be integrated in real time, which has an impact on reducing waste instantly through real-time readings from gas timer and other wastes. The use of artificial intelligence algorithms enhances economy, saves effort, and makes important decisions more comprehensive.

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