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The Role of Artificial Intelligence Techniques in Enhancing Project Completion Speed: A Study on Using LSTM Networks for Predicting Delay Times

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Abstract:

This study aimed to investigate mechanisms for enhancing project completion speed through the application of artificial intelligence techniques. The study adopted the approach of "Using LSTM Networks for Predicting Project Delay Times," and the researchers utilized data from 3530 residential units for training, testing, and prediction. Selecting project delay times as a focus was driven by their significant impact on vital project completion. The research problem centers around the main question, "Can LSTM networks be successfully used to predict project delay times?" The significance of the study lies in utilizing Long Short-Term Memory (LSTM) neural network techniques to improve the prediction of project delay times, thereby enhancing project planning and management, reducing delays, and increasing efficiency in execution. Among the key findings, it was revealed that LSTM networks can effectively enhance the prediction of construction project delay times, exhibiting high accuracy and retrieval rates. Introducing this advanced technology to project management can lead to improved scheduling, planning, and reduced delays, ultimately contributing to enhanced work efficiency, productivity, and more accurate strategic decision-making.

Research Type: Research Paper.
Keywords: Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Artificial Neural Networks (ANN), LSTM Networks, Project Management (PM), Delay Times (DT).

1. Introduction:

Currently, Artificial Intelligence (AI) stands as one of the most extensively studied and advanced innovations in recent years. It spans from the tools and technologies employed in our daily lives to the realm of self-driving cars and sophisticated personal devices. Consequently, AI has swiftly assumed the role of users in real-world applications, driving rapid progress. At present, a comprehensive reevaluation of all tasks performed by humans is underway, propelled by the advancement of algorithms, robotics, cognitive tools, and smart devices. This has led to the emergence of the term "AI partner" to describe the evolving human-machine relationship (Arup, 2018). Notably, one of the significant areas undergoing reassessment is project management. The integration of the scientific revolution into the practices of high-level managers in this field is pivotal to achieving success and objectives across diverse projects. This includes accelerating timely completion while minimizing costs and elevating quality standards.

Despite the gradual replacement of numerous professions by intelligent systems, the profession of project management remains essential, albeit in collaboration with these evolving systems (Elrajoubi, 2019). Additionally, the construction and building sector emerges as one of the most crucial industries, directly influencing governments and economies through its impact on both economic vitality and the lives of citizens. This sector serves as a substantial source of employment and indirectly generates job opportunities across various sectors. Such dynamics contribute to economic growth and an increase in the gross domestic product (GDP). Furthermore, the construction sector plays a fundamental role in shaping a country's infrastructure, encompassing critical elements like bridges, roads, airports, and public facilities. By fostering the ability to attract investments and stimulate business development, it serves as a cornerstone for infrastructure enhancement and advancement.

1.1 Literature review:

Construction projects are highly complex undertakings, making them susceptible to delays due to the impact of numerous uncertain factors. Recent research is increasingly focusing on utilizing Artificial Intelligence (AI) techniques to analyze historical data and develop predictive models for construction project delays. With the emergence of Artificial Neural Networks (ANNs) as a prominent AI approach, they have provided non-linear modeling capabilities to address intricate problems in the real world. In a previous study, Boussabaine (1999) and colleagues utilized Artificial Neural Networks (ANNs) to estimate the duration of a construction project based on factors such as scope, resources, and environmental elements. The model they developed demonstrated superior performance compared to traditional multiple regression analysis, indicating its suitability for modeling project uncertainties.

Meanwhile, Tah et al (1999) developed an Artificial Neural Network (ANN) model using scheduled timeline data to predict the actual project duration, achieving an accuracy exceeding 90% in test data. They highlighted the potential of using ANNs to model the complex relationships among project features. Artificial Neural Networks (ANNs) have shown promise in modeling project timelines.

In another study, Cheng et al (2019) conducted a study that introduced a neural network short-term memory model (NN-LSTM) for accurate estimation of the remaining time-to-completion (ESTC) schedule in construction projects. The model considers both sequential and non-sequential factors, utilizing a database of 226 cases from 11 educational game construction projects. The NN-LSTM model showed strong performance, with MAPE below 5% and MAE of 2%. It outperformed EVM formulas and other AI-based models, offering reliable solutions for innovative project management. While Jang et al. (2019) conducted a study to predict the failure of construction projects using the Long-Term Memory (LSTM) network. The LSTM model has excelled in predicting business failure for building contractors.

Dong et al (2020) employed Long Short-Term Memory Neural Networks (LSTM NN) to predict construction cost indicators. The aim of this study was to explore the capabilities of neural networks in forecasting engineering project costs, thereby identifying research gaps in this domain. A set of indicators for predicting project costs in the Republic of China was determined. The proposed model demonstrated superior performance, affirming its ability to predict construction project cost indicators. Additionally, the researchers provided guidelines for selecting prediction algorithms and model parameters. In a study conducted by Le et al (2020), the Long Short-Term Memory (LSTM) network was employed for predicting project completion costs. The study involved a comparison between the LSTM predictions and the cost estimates derived from Earned Value Management (EVM) techniques for project cost prediction. The findings of the study confirm the efficacy of the LSTM network in achieving accurate predictions.

The study by Liao and Chen (2021) demonstrated the superiority of the deep learning algorithm using LSTM network in predicting time sequence data for IoT. In a study conducted by Chen et al. (2022), the Long Short-Term Memory (LSTM) technique was employed to extract temporal sequence information of network behaviors, yielding the best predictive outcome. Additionally, LSTM was successfully utilized to capture temporal sequence information of behaviors, with results demonstrating higher accuracy compared to other deep learning and machine learning methods.

Finally, Chen and HE (2023) conducted a study aiming to predict structural changes in tunnels during construction and operation using neural network techniques, specifically Long Short-Term Memory (LSTM). The model demonstrated its superiority over traditional methods in settlement prediction, as evident from performance comparison.

Previous studies have primarily concentrated on forecasting project durations, while limited work has addressed the binary classification task of predicting the likelihood of delay based on planned project features. The research problem is to "enhance the accuracy of predicting construction project delay times using an LSTM neural network model: a study on improving the predictive performance of the model built on historical project data to achieve more precise identification and prediction of delay occurrences. This study focuses on addressing the challenges associated with long-term temporal dependencies and unforeseen changes within the construction context." This study aimed to address this gap by developing LSTM models on a construction industry dataset and conducting an evaluation of their delay classification capabilities. The results will provide data-driven insights into the suitable artificial intelligence techniques for predicting construction project delays.

2. Material and Methods:

The Researchers relied on data collection, and tools to conduct the research, as follows:

1.The data was collected from 49 residential buildings in an existing project. The buildings consist of 17 floors, with some containing 6 residential apartments and others containing 5. Due to the insufficient quantity of data for deep learning techniques in the created model, data from other projects of the same category was utilized, resulting in a total dataset of 3,530 additional housing units. This data was obtained from the Kaggle website (https://www.kaggle.com/datasets), a subsidiary of Google specializing in providing data sources and machine learning resources. Kaggle offers processed and organized data for exploration, creation, and deployment of models.

2.Python programming language was employed for the execution and construction of the artificial intelligence model using the Long Short-Term Memory (LSTM) network. The adoption of this approach is attributed to its widespread acceptance among researchers due to its result accuracy and the availability of numerous pre-existing and essential libraries for model development (Lomakin, et al, 2020; Sezer, et al, 2020; Halim, et al, 2021).

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3. Using the work environment Google Colab platform is highlighted as it offers an online environment for Python code execution and development without the need for local setup. Similar to development environments like Jupyter Notebook, Google Colab provides central processing units, graphical capabilities, and interactive execution of codes and data analysis through the browser. This web-based service simplifies users' ability to perform experiments and analyze data interactively, without the necessity of configuring intricate development environments on their local devices.

4. Initial Data Description: After collecting the research data, the identified variables in Table (1) were determined for input into the model, as illustrated in Table (2), where a portion of the data was extracted from an Excel spreadsheet:

Table (1) Illustrates the Variables of the Used Data

N	Variables	Details
1	"built_area"	Building area in square meters, and summarizing the floors in the case of a multi-story building.
2	"modul_price"	Raw building cost per square meter.
3	"weeks_duration"	Total duration of the construction project in weeks.
4	"weeks_delay"	Total delay of the construction project in weeks.
5	"typology"	Building classification: commercial, residential, government buildings, etc.

Table (2) Illustrates the Dataset Utilized in the Research.

	A	B	C	D	E	F	G	H
1	built_area	modul_price	weeks_duration	DETACHED	COLLECTIVE	COMMERCIAL	OTHERS	DELAYED
2	-1.417358938	-0.581123221	-0.490790026	1	0	0	0	1
3	-1.427223221	0.118484141	-0.490790026	1	0	0	0	1
4	-1.439186204	-0.619744127	-2.009743378	1	0	0	0	0
5	-1.42131205	-1.151821975	-0.441791531	1	0	0	0	1
6	-1.411546711	-0.761155734	-1.911746387	1	0	0	0	0
7	-1.431730716	1.098239658	-1.27476595	1	0	0	0	1
8	-1.430768115	-0.888858463	-0.392793036	1	0	0	0	1
9	-1.42487763	0.891649574	-0.931776483	1	0	0	0	1
10	-1.391015182	-0.219268664	-0.24579755	1	0	0	0	1
11	-1.387345254	0.023339549	-0.882777988	1	0	0	0	1
12	-1.430407004	0.241932773	-1.127770464	1	0	0	0	0
13	-1.398279845	-1.004236601	-0.637785512	1	0	0	0	0
14	-1.398006296	0.543129862	-1.37276294	1	0	0	0	1
15	-1.432806586	1.02944739	-0.882777988	1	0	0	0	1
16	-1.429004305	-0.488517249	-1.176768959	1	0	0	0	1
17	-1.368534967	-0.471031409	-1.27476595	1	0	0	0	0
18	-1.438865144	-0.152619045	-1.323764445	1	0	0	0	1
19	-1.366534626	0.404496718	-0.882777988	1	0	0	0	0
20	-1.407330097	1.196804246	-0.784780998	1	0	0	0	1
21	-1.405386605	-1.34399026	-0.196799055	1	0	0	0	1
22	-1.389434215	-1.389281244	-1.029773474	1	0	0	0	0
23	-1.421993676	-1.798727323	-1.127770464	1	0	0	0	1
24	-1.432371965	-0.835899672	-0.882777988	1	0	0	0	0
25	-1.437030828	0.413401796	-0.784780998	1	0	0	0	1
26	-1.416092506	0.891041168	-1.27476595	1	0	0	0	1
27	-1.384888102	-0.351861037	-1.127770464	1	0	0	0	0
28	-1.378592365	0.554058544	-1.127770464	1	0	0	0	0

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	A	B	C	D	E	F	G	H
3504	0.207717258	-0.741816327	-1.029773474	0	0	1	0	1
3505	0.093644677	-0.501370416	-0.833779493	0	0	1	0	1
3506	-0.455096773	-1.26221226	-0.196799055	0	0	1	0	1
3507	0.897178364	-0.208902501	0.195188906	0	0	1	0	0
3508	0.211123427	-0.835049877	-0.490790026	0	0	1	0	0
3509	0.325754047	-0.791952874	-0.441791531	0	0	1	0	0
3510	-0.991562236	0.24808582	0.146190411	0	0	1	0	1
3511	-0.484672669	-0.060271492	-0.14780056	0	0	1	0	0
3512	-0.908378014	-0.686684266	-0.343794541	0	0	1	0	0
3513	-0.306597051	-0.816826099	0.097191916	0	0	1	0	0
3514	-0.616671553	-1.134134357	-0.04980357	0	0	1	0	0
3515	0.709883083	-1.180195867	-0.196799055	0	0	1	0	0
3516	0.354175322	-0.791161118	-0.392793036	0	0	1	0	0
3517	0.170867121	-0.279784339	-0.784780998	0	0	1	0	1
3518	0.303981195	-0.557802619	-0.931776483	0	0	1	0	1
3519	-0.801128376	-1.02430649	-1.323764445	0	0	1	0	0
3520	1.337379723	-0.814253727	-0.735782502	0	0	1	0	0
3521	-0.648291002	-0.748599381	0.146190411	0	0	1	0	0
3522	-0.447015453	-0.23943437	-0.784780998	0	0	1	0	1
3523	-0.697128558	-0.273496464	-1.029773474	0	0	1	0	0
3524	0.078783862	0.243578155	-0.588787017	0	0	1	0	0
3525	1.136704035	-1.083435507	-0.24579755	0	0	1	0	1
3526	-0.819531166	-0.690494461	-1.519758426	0	0	1	0	1
3527	0.924999901	-0.799381596	-0.04980357	0	0	1	0	0
3528	-0.218178406	-0.84474721	0.293185897	0	0	1	0	0
3529	0.549232103	-0.319414281	0.048193421	0	0	1	0	0
3530	0.160079742	0.066053959	1.126160315	0	0	1	0	0
3531	-0.458429438	-0.691472934	-0.14780056	0	0	1	0	0

5. Input and Output Specification: The inputs and outputs were determined based on the values mentioned and outlined in Table (2). Accordingly, the network consisted of eight input elements or neurons, while the output consisted of a single element (neuron) representing the delay.

6. Mathematical equations: Mathematical equations for performing the set of calculations related to the model: (Accuracy, Recall, Precision, F- measure, Specificity) (Ilwani et al, 2023), (Moreno et al, 2023).

2.1 Implementation of ML in Python

Before delving into the explanation of the steps for implementing the neural network, we elucidate the components of the study model as depicted in Figure (1). This model comprises input variables, the utilized neural network model (LSTM), and the output variable. The training was executed through the following steps, also illustrated in Figure (2):

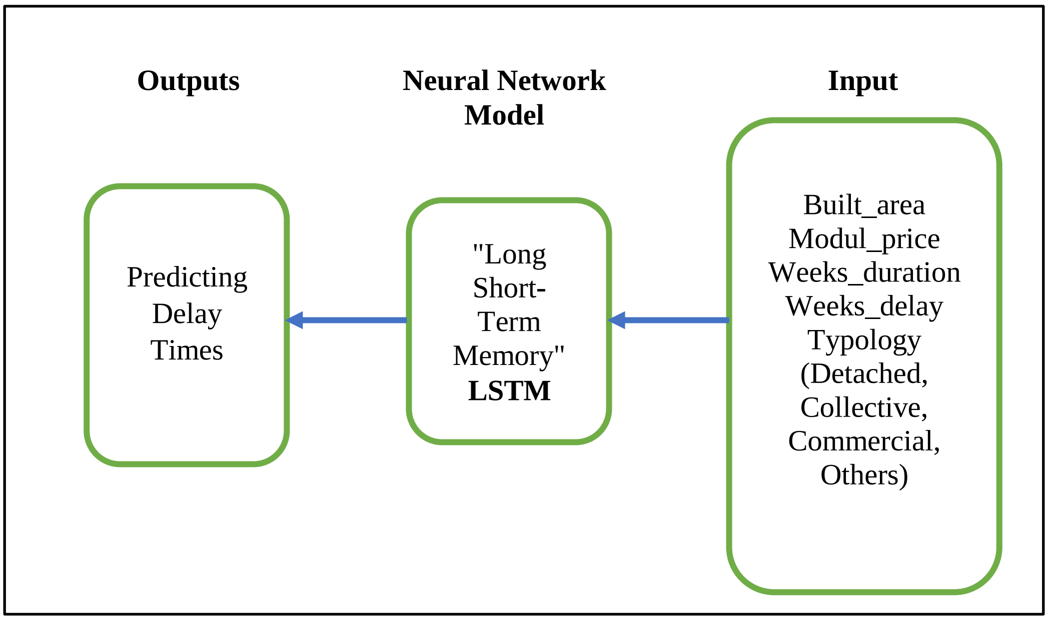

Figure (1): Components of the Study Model
Source: Prepared by the researchers

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1. Organizing, structuring, and installing certain libraries using Python in the Colab Notebooks environment, and importing the following libraries: numpy, pandas, sklearn, matplotlib, TensorFlow, and seaborn.
2. Loading the dataset stored in an Excel file into a numpy array.
3. Splitting the dataset into X and Y components. Where X represents the input data from columns 1 to 7, and Y represents the target data from a single column labelled "DELAYED".
4. The dataset X and Y were divided into training and testing sets, with a chosen ratio of 70% for training and 30% for testing, using the following programming code:

```
X_train, X_test, y_train, y_test = train_test_split( X, Y,
test_size=0.30, random_state=42)
```

5. Building the Machine Algorithm, the first step is:
1. Importing libraries and packages.
2. Initializing the algorithm.

6. Initiating the Machine Algorithm Training:
1. Compiling the machine algorithm, according to the following programming code:

```
model. Compile(loss=['mse'], optimizer="adam",
metrics=["accuracy"],)
```

2. Matching the machine algorithm to the training dataset, according to the following code:

```
history =model.fit(X_train, y_train, validation_data=(X_test, y_test), batch_size=batch_size,
epochs=10,verbose=0,)
```

7. Predicting the Results of the Test Set.
8. Constructing the Confusion Matrix is a commonly used tool in evaluating classification and machine prediction models. This matrix is employed to measure the model's accuracy in representing classes and determine whether it correctly classifies or not. This matrix allows for a systematic and comprehensible correction of true and false errors. The matrix relies on four fundamental terms, as illustrated in the following Table (3).

Table (3): Confusion Matrix Terminology

n	Term	Meaning
1	True Positive (TP)	Cases that were correctly predicted and were indeed true.
2	True Negative (TN)	Cases that were correctly predicted but were false in reality.
3	False Positive (FP)	Cases that were incorrectly predicted and were true in reality (false positives).
4	False Negative (FN)	Cases that were incorrectly predicted and were false in reality (false negatives).

Through this matrix, performance metrics such as accuracy, sensitivity, specificity, and F1-score can be calculated to evaluate the model's performance. The F1-score provides a value between 0 and 1, where 1 represents the model's ideal performance (full precision and recall), while a value of 0 indicates that the model is either inaccurate or completely insensitive. This value serves as a useful measure of the overall model performance, especially when class imbalances exist within the dataset.

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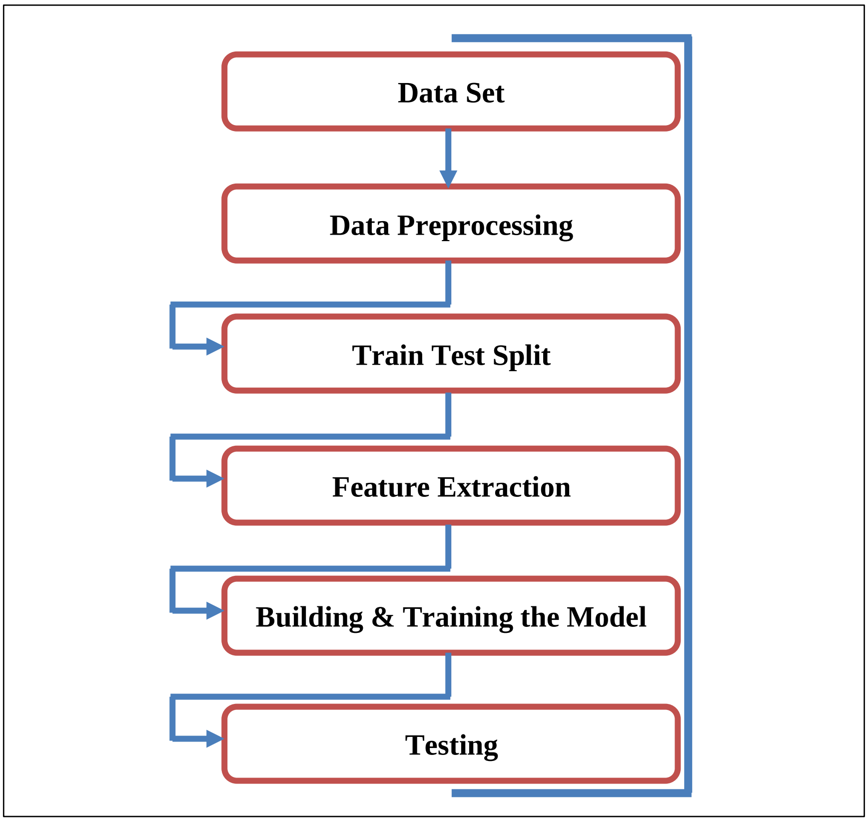

Figure (2): Steps of Training Implementation
Source: Prepared by the researchers based on the information above.

2.2 Artificial Intelligence (AI):

In recent decades, the world has witnessed a remarkable advancement in the field of Artificial Intelligence (AI), making it one of the most prominent and extensively investigated areas of research and innovation. Artificial Intelligence relies on the utilization of innovative techniques and algorithms to emulate human cognitive capacities, such as learning and inferential thinking. The scope of Artificial Intelligence encompasses the design of systems and software enabling computers to perform tasks including analysis, interpretation, and decision-making. According to Al-Azam (2021), the aim of Artificial Intelligence is to study the behavior of intelligence in humans and machines, in order to achieve the development and embodiment of such behavior in artificial systems.

The utility of Artificial Intelligence manifests in its capacity to comprehend intricate and previously unaddressed topics through scientific analysis. It engages in crucial discussions, such as the concept of thinking entities, and extends its reach to matters concerning significant decision-making and the generation of novel ideas (Whitby, 2008). The rapid scientific progress in this field continues to advance swiftly, particularly in the technological aspects of AI (UNESCO, 2018). The concept of AI refers to the utilization of computer devices, enabling them to imitate and simulate cognitive functions of human perception (Lahlah, 2020). The foundational principle underpinning Artificial Intelligence is information processing (Qamora et al, 2018). Determining its intended purposes, while ensuring interaction with humans that may be indistinguishable from human emotions, poses a significant challenge (Abdelaziz et al, 2019). The importance of Artificial Intelligence has increased with the growth of large-scale data storage and its utilization through statistical and probabilistic methods, which form the basis of artificial intelligence operations (Al-Rawi and AL-sarraf, 2020).

According to Marvin Lee Minsky, Artificial Intelligence is defined as a computer program that performs tasks and accomplishes them in a manner resembling human achievement. It is also considered a scientific system encompassing engineering methods known as intelligent devices and software (Musa and Bilal, 2019), While defined by Vella (2020) as the technology that enables computers to mimic human intelligence through the use of rules, logic, machine learning, and decision tree structures, As defined by Fridgeirsson et al (2021), artificial intelligence is a system that comprehends data with high precision and utilizes it to achieve specific and desired objectives through a learning process derived from that data. International Finance Corporation (IFC) (2021) defines it as a scientific discipline that empowers machines to operate intelligently, simulating human intelligence through smart methods across various aspects of modern life, with the goal of enhancing productivity and improving service delivery. While defined by Sejera and Bocarnea (2022) as a modern field within the realms of engineering and sciences, it focuses on the development and implementation of intelligent behavior for computer systems, including machine thinking, visual capabilities, knowledge representation, machine learning, natural language processing, and robotics design.

The researcher defined artificial intelligence as a methodology that enables computers to enhance their capabilities in thinking and transforms inert devices into systems that simulate human capacities in learning, reasoning, prediction, achieving rapid and precise performance. This methodology relies on a diverse array of integrated technologies to empower machines with understanding, perception, decision-making, and learning experiences at a level approaching human capabilities.

2.2.1 Machine Learning (ML):

Machine Learning (ML), referred to as an abbreviation, is a subset of artificial intelligence that utilizes algorithmic models and employs statistical methods with the ability to learn with or without explicit programming (Jariwala et al, 2023). It is considered one of the most important branches of artificial intelligence, relying on the use of data and algorithms to acquire knowledge, akin to human behavior. Naturally, its accuracy gradually improves with the advancement of data science. Algorithms are trained using statistical techniques, and these algorithms express the ability to perform classifications and predictions, in addition to extracting key insights for data refinement. These insights contribute to decision-making within companies through conducted analyses, leading to the expansion of frameworks and key indicators. This importance is amplified, particularly with the increasing volume of massive datasets, which consequently escalates the demand for data science specialists (AL Qady and Kandil, 2010). ML learning techniques are used to solve various problems, including (Tyralis and Papacharalampous, 2022): Classification, Anomaly Detection, Regression techniques, Clustering Techniques, and Reinforcement technique (Ilwani et al, 2023).

2.2.2 Deep Learning (DL):

Deep neural networks are considered a part of the field of machine learning. They consist of structures containing multiple layers of neurons, typically including three layers or more (Bloch and Sacks, 2018). The purpose of these networks is to emulate human thinking capabilities, enabling them to absorb knowledge from a wide range of massive datasets. The hidden layers in these networks enhance the accuracy of predictions and classifications (Ramou, 2019). The application of machine learning improves automation processes without human intervention and is evident in various services, such as remote-control devices and credit card fraud detection (Mustafa, 2022). The multiple layers of deep neural networks influence each other, with the performance of each layer affecting the layer that precedes it. This process is known as forward propagation. The input layers refer to the stage where models receive data for processing, while the output layer is responsible for final prediction and classification (Borrmann et al, 2006).

2.2.3 Artificial Neural Networks (ANNs):

ANNs are composed of a collection of nodes, where each node performs a specific type of computation collectively. Each of these nodes is a small computational unit, operating in parallel and interacting with each other. The neural network is defined as a mathematical model that emulates the characteristics of biological systems and processes information in a parallel manner. It consists of relatively simple elements called neurons (Ramou, 2019). Neural networks have become widely used in various fields (Pan et al, 2022), such as image classification (Li et al, 2021), prediction, object detection, and natural language processing (Pater and Mitici, 2023). Odewahn et al. (1992) defined them as a set of artificial intelligence techniques capable of performing challenging pattern recognition tasks, inspired by biological neural networks.

These networks, also known as artificial neural networks, are models inspired by the human brain and are utilized for extracting patterns of information from multidimensional domains. They excel in their ability to store and utilize empirical knowledge through parallel and distributed processes (Kalogirou and Bojic, 2000). It generally consists of three levels: the input level, the hidden level, and the output level (Nazim, 2009).

The researchers defined artificial neural networks as models inspired by the human brain used for learning and extracting patterns of information from various domains. These networks rely on organizing layers of neurons to process data and extract knowledge. There are several types of artificial networks, and the focus will be on (LSTM) as the researchers used this type.

2.2.4 Neural Network Long Short-Term Memory (LSTM):

LSTMs are a specialized and advanced type of Recurrent Neural Network (RNN) that employ hidden units for analyzing streaming data (Ashour, 2022). They are utilized in deep learning and consist of a series of connected cells referred to as "memory blocks." These blocks encompass gates (input, output, forget) through which data is identified for storage duration, retrieval timing, and content, enabling the network to learn how to manage its memory. These gates play a pivotal role in monitoring and controlling the network's operations. They allow the network to determine what information should be disregarded, what should be stored, and what should be output. These gates are as follows (Mahdi and ALmohana, 2022):

1. Input Gate: The input gate equation in Long Short-Term Memory (LSTM) networks is utilized to determine the values that need to be updated in the current cell state based on the current input and the previous hidden state. This gate contributes to determining the extent of the new input's influence on the current state.

$$\mathrm{it} = \sigma\ \mathrm{Sigmoid}\ (\mathrm{Wi} \cdot [\mathrm{ht} - 1, \mathrm{xt}] + \mathrm{bi}) \qquad (1)$$

Where:

- i_t: is the input gate at time t.
- σ: Sigmoid activation function.
- W_i: is the weight matrix for the input gate.
- $h_t - 1$: is the previous hidden state.
- X_t: is the current input.
- b_i: Bias term for the input gate.

The input gate (ti) contains values ranging between (0 and 1), representing the extent of the current input's impact on updating the current state. If the value of (ti) is close to zero, it indicates that the new input should be ignored. Conversely, if the value of (ti) is close to one, it suggests that the new input should have a significant impact on updating the current state.

2. Forget Gate: The forget gate in Long Short-Term Memory (LSTM) networks is responsible for making decisions regarding what information to discard or retain from the previous cell state. It takes input from the previous time step (or hidden state) and the current time step, and processes it through the sigmoid activation function.

$$\mathrm{ft} = \sigma\,(\mathrm{Wf}\,[\mathrm{ht}-1, \mathrm{xt}] + \mathrm{bf}) \qquad (2)$$

Where:

- ft: Output of the forget gate at time (t).
- σsigmoid: Sigmoid activation function.
- Wf: Weight matrix associated with the forget gate.
- ht−1: Previous hidden state (output) at time (t-1).
- xt: Current input at time (t).
- bf: Bias term for the forget gate.

The output of the forget gate, ft, is a value between 0 and 1 for each element in the cell state. It acts as a filter, enabling the LSTM network to determine which information from the previous state should be retained and which should be forgotten based on the current input and the previous hidden state.

3. Output Gate: The output gate in Long Short-Term Memory (LSTM) networks is utilized to determine the final output at the current time step based on the current memory cell state and the current input. The output gate identifies which components of the current state will be utilized in the ultimate output.

$$\mathrm{Ot} = \sigma\,(\mathrm{Wo}\cdot[\mathrm{ht}-1, \mathrm{xt}] + \mathrm{bo}) \qquad (3)$$

Where:

- Ot: Output of the output gate at time (t).
- σsigmoid: Sigmoid activation function.
- Wo: Weight matrix associated with the output gate.
- ht−1: Previous hidden state (output) at time (t-1).
- xt: Current input at time (t).
- bo: Bias term for the output gate.

The output gate, Ot, determines the value of the current unit's output based on the current hidden state and input. This output represents the value that will be sent out for use in the specific task, such as prediction or classification.

4. The Cell State: Equation in Long Short-Term Memory (LSTM) networks expresses how to update and maintain the cell state over time. The cell state is a crucial component of LSTM, carrying information across time sequences and contributing to the representation of continuous knowledge.

$$\mathrm{Ct} = \mathrm{ft}\cdot\mathrm{Ct}-1 + \mathrm{it}\cdot\mathrm{C{\sim}t} \qquad (4)$$

Where:

- Ct: Cell state at time (t).
- ft: Output of the Forget Gate at time (t), determining the extent of retaining previous information in the current state.
- Ct−1: Previous cell state at time (t-1).
- it: Output of the Input Gate at time (t), specifying the amount of new signal to be added to the current state.
- C~t: Proposed update signal to the current state at time (t), calculated based on the current input and hidden state.

The Cell State Equation demonstrates how previous information is combined with new information to update the current cell state. This enables the LSTM network to effectively store and propagate knowledge over time, adapting it according to changing requirements in the task.

5.The equation to compute the new hidden state (output vector) in the context of a Long Short-Term Memory (LSTM) network can be explained as follows:

$$ht = ot \cdot \tanh(Ct) \qquad (5)$$

Where:
- ht: The new hidden state or output vector at the current time step.
- ot: The output of the Output Gate at the current time step, which determines the extent to which the cell state information is used in generating the output.
- tanh: The hyperbolic tangent function, a non-linear activation function that scales the values of the cell state to be between -1 and 1.
- Ct: The cell state at the current time step, which contains information from both the previous cell state and the current input.

In summary, the equation computes the new hidden state by multiplying the output of the Output Gate with the hyperbolic tangent of the current cell state. This helps determine the final output of the LSTM unit, which can be used for various tasks such as prediction, classification, or any other application where sequential data processing is needed.

2.3 Project Management:

The rapid growth of businesses generates significant pressures on organizations to achieve their strategic objectives effectively, with minimal cost, and complete success. To ensure the successful accomplishment of these goals, it is undoubtedly necessary to identify the means that ensure the alignment of efforts among all relevant parties and coordinate their interactions efficiently (Al-Ilm, 2018), Project Management (PM) is set to dominate the future management approaches due to its unique characteristics that make it one of the most responsive management styles to the rapidly changing business environment. Therefore, it must deal with the distinct and non-repetitive characteristics of projects, which consist of a series of interconnected and integrated activities. Additionally, projects are characterized by their temporary nature and the continuous changes in tasks and conditions, necessitating quick and innovative responses to ensure the project's adherence to requirements, resources, and constraints (Najm, 2013), Project management forms the foundation for achieving success and excellence in organizations, as it provides the necessary support for organizations to confront challenges, environmental changes, and risks that surround them (Kebro, 2017), Al-Afandi (2019) defined project management as the process of guiding individuals with the capability to execute and plan project tasks through a series of activities, ensuring their execution within the specified schedule and budget, While Qais (2020) defined it as the process in which available skills and knowledge are implemented and techniques are utilized in project activities with the aim of fully achieving its requirements, El Khatib et al (2020) defined it as a supervisory function that aligns with the organization's structure and aims to monitor and manage the processes of the project life cycle, According to Abulawi (2022), project management is defined as a collection of processes, duties, roles, and tasks related to the creation of projects, with the aim of efficiently and effectively achieving project goals. This is done in accordance with specified standards that outline the project's path through its various stages, encompassing aspects of time, quality, and cost. The researchers defined project management as the utilization of the best skills, tools, and knowledge to manage operations and activities in order to achieve the objective and complete the project in the shortest time, at the lowest cost, and with the highest possible quality.

2.3.1 Fundamentals of Project Management:

Project managers require significant and focused efforts to comprehend the most crucial elements that lead to the success of projects (Al-Samara'i and Al-Hasnawi, 2016), The core principles of project management revolve around the well-known constraints often referred to as the "iron triangle," consisting of time, quality, and cost, as well as scope, as illustrated in Figure (3) (Association for Project Management, 2020). These elements constitute fundamental aspects in the field of project management and serve as a central focal point for the attention and efforts of project managers (Ahmed, 2018).

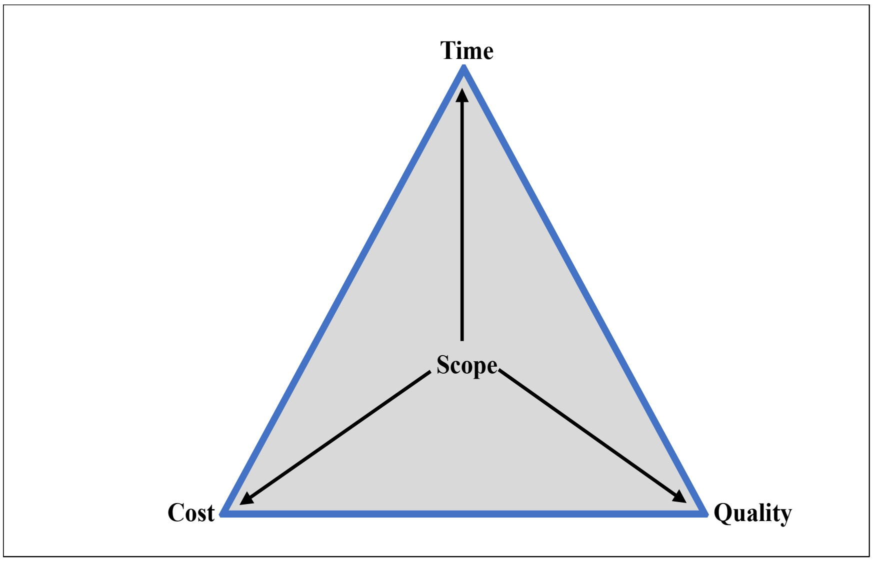

Figure (3): represents the Project Management Triangle.
Source :Association for Project Management, 2020, APM Body of Knowledge, Vol 7th edition, UK

2.4 Delay:

The term "delay" is used to refer to the postponement of a specific event or the execution of a particular activity beyond the expected time. This concept is widely recognized across various fields and industries, including engineering, project management, and technology. It can result in negative effects on work schedules and the achievement of desired objectives. Unexpected changes, external factors, and organizational deficiencies are among the reasons behind delays. Enhancing management practices and minimizing delays play a crucial role in ensuring the successful execution of activities and projects, adhering to predefined timelines.

Researchers Assaf and Al-Hejii (2006) define delay as "exceeding the stipulated time in the contract or surpassing the date agreed upon by the parties for project delivery". Sambasivan and Soon (2007) define it as a condition where the completion of a specific project is hindered due to factors related to the executor (contractor), consultant, or client, along with other agreed-upon reasons according to their conducted research.

Furthermore, researchers have defined time delay as the non-compliance with the triple constraints of the project (time, cost, and quality) agreed upon within the contractual framework between the concerned parties (owner and executor).

3. Discussion of Results:

3.1 Results:

The LSTM model was trained on the research data, and the researchers found that accuracy improves while the loss decreases, as evident from the LSTM plot shown in Figure (4).

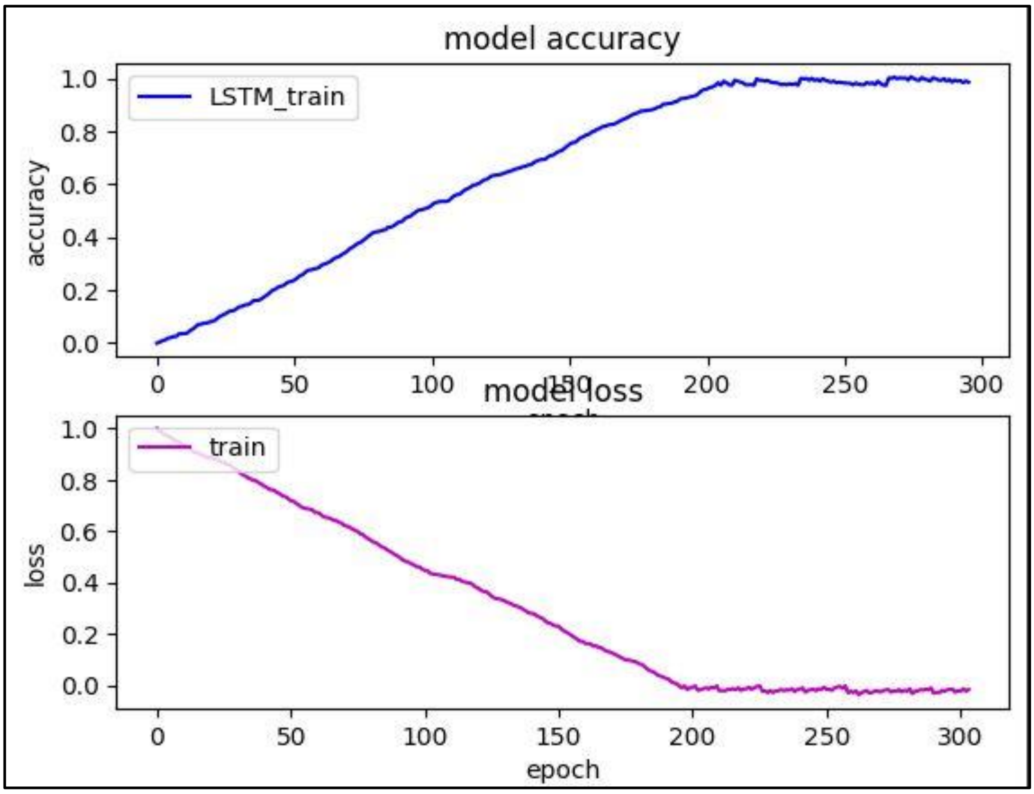

Figure (4): LSTM Training
Source: Based on Python Outputs

The Long Short-Term Memory (LSTM) model succeeded and outperformed, showcasing exceptional performance in accurately detecting delayed projects. This is evident from the outstanding recall metric*, which signifies the model's capability to correctly and precisely identify all delayed projects. It is apparent that LSTM's effective strength in analyzing sequential temporal data makes it highly suitable for classifying construction project delays based on the planned timeline features. These findings confirm the promise of LSTM networks in forecasting project delays through the analysis of initial project plans. This model can be utilized to assess delay risks and achieve mitigation by prioritizing scheduling or resource allocation.

"*Recall*"* is a metric used to assess the performance of classification models, such as neural networks. It focuses on the model's ability to identify and detect all true positive cases (projects that are actually delayed) among the total count of true positive and false negative cases (non-delayed projects) that were predicted (Powers, 2011).

3.2 Evaluation:

The "evaluation" process is a critical step in the realm of scientific research, particularly when implementing neural network models. This process encompasses assessing the performance and effectiveness of the model developed in data processing and analysis, as well as making predictive decisions. Utilizing various metrics such as accuracy and recall rate, the evaluation aims to measure the model's capability to achieve desired outcomes in tasks of data classification and prediction. By meticulously evaluating the model's performance, researchers gain insights into its strengths and weaknesses, thereby facilitating informed decision-making and potential enhancements for subsequent model improvements.

3.2.1 Accuracy:

It is a metric used to assess the performance of a model, including artificial neural networks. Accuracy aims to measure the model's ability to classify data correctly. Accuracy represents the ratio between the number of correctly predicted instances by the model and the total available instances for classification. This is calculated using equation number (6).

$$\text{Accuracy} = \frac{\text{Correctly classified instances (TP + TN)}}{\text{Total instances (TP + TN + FP + FN)}} \times 100\% \qquad (6)$$

Where:
- TP + TN: The number of cases correctly classified.
- (TP + TN + FP + FN): The total number of cases.

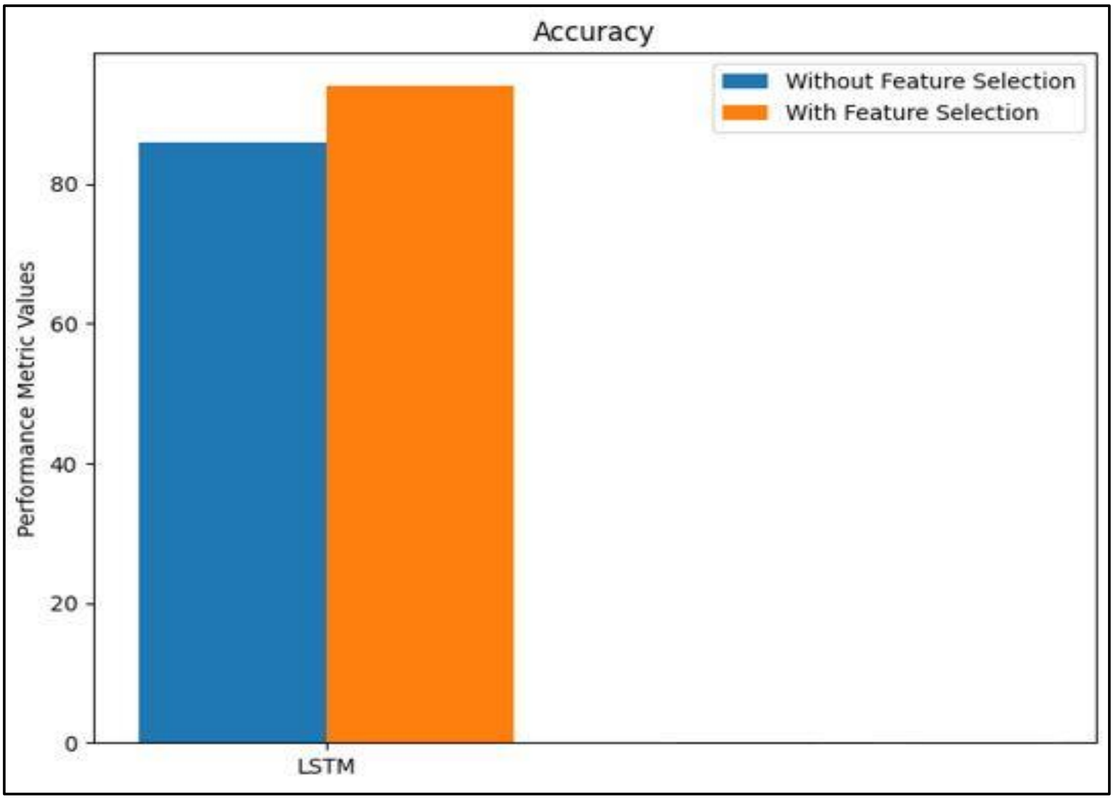

Figure (5): Prediction Accuracy of LSTM Model
Source: Based on Python Outputs

Figure (5) illustrates the prediction accuracy of Long Short-Term Memory (LSTM) models in learning and forecasting (performance testing) in general. This is manifested through the blue column, which represents learning and forecasting using all input variables. On the other hand, the orange column represents learning and forecasting using specific variables and a designated objective. It relies on the last column in the data, which represents the delay time.

3.2.1 Specificity:

It is a performance metric that measures the model's ability to correctly identify negative cases or outcomes that are not of interest. Specifically, this metric assesses the proportion of true negative cases that are correctly classified as negative among the total available negative cases. In other words, it is a measure that helps evaluate the model's capability to distinguish between cases belonging to the negative class and those that are not, without mistakenly categorizing them as positive cases. This is particularly important in scenarios where the negative class holds significant importance, as misclassifying negatives can have significant implications. It is calculated as a percentage and can be expressed using Equation (7).

$$\text{True Negative Rate (Specificity)} = \frac{\text{TrueNegative (TN)}}{\text{True Negative (TN)} + \text{FalsePositive(FP)}} \times 100\% \qquad (7)$$

Where:

- True Negative (TN): represents the number of negative cases that were correctly classified by the model as negative.
- False Positive (FP)represents the number of negative cases that were incorrectly classified by the model as positive.

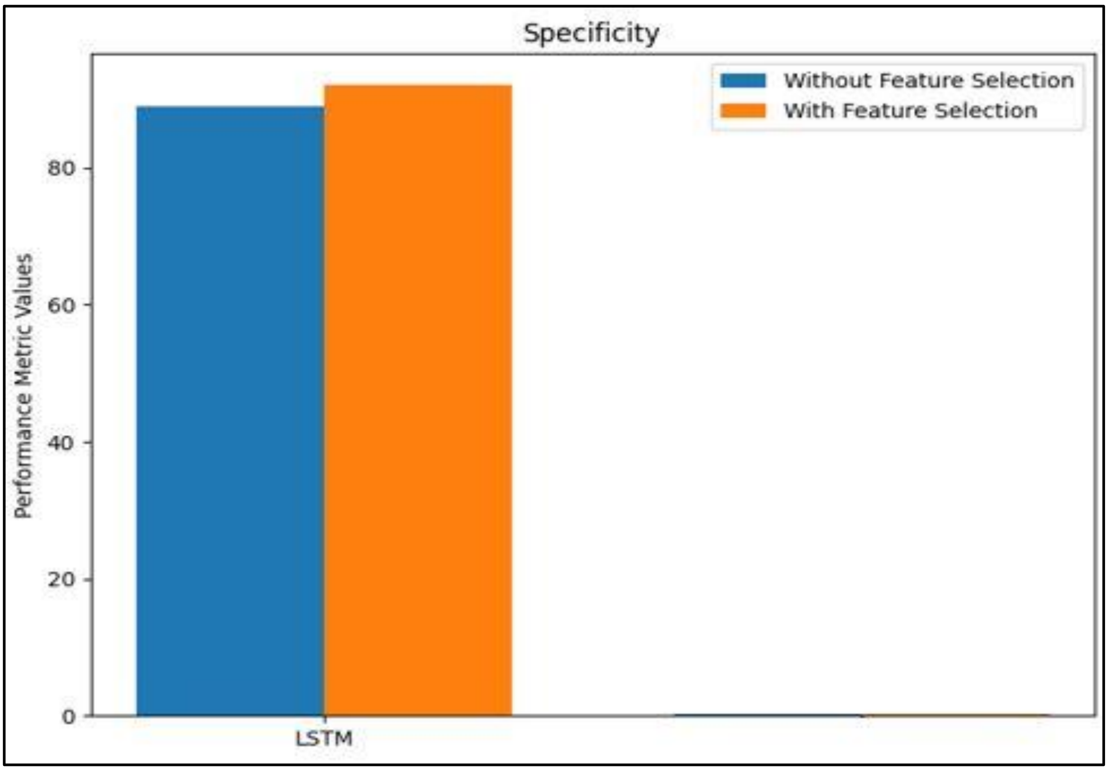

Figure (6): LSTM Model Specificity
Source: Based on Python Outputs

Figure (6) illustrates the Specificity rate of the LSTM algorithm in learning and prediction (performance testing) processes in a general sense. This is manifested through the blue column, representing learning and prediction using all input variables. Meanwhile, the orange column represents dependency on specific values and a specific objective, relying on the last column in the data, which represents the delay time.

3.2.2 Sensitivity:

Sensitivity**,** also known as True Positive Rate or Recall Rate, measures the model's ability to correctly identify positive cases among the actual positive cases. It quantifies the proportion of true positive cases that are correctly classified as positives out of the total actual positive cases available for classification. Sensitivity is particularly important in scenarios where positive cases are of significant importance, as misclassifying positive cases can have important implications. It is calculated as a percentage and can be expressed using Equation (8).

$$\text{True Positive Rate (Sensitivity)} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Negative (FN)}} \times 100\% \qquad (8)$$

Where:

- True Positive (TP): represents the number of positive cases correctly classified as positive by the model.
- False Negative (FN): represents the number of positive cases incorrectly classified as negative by the model.

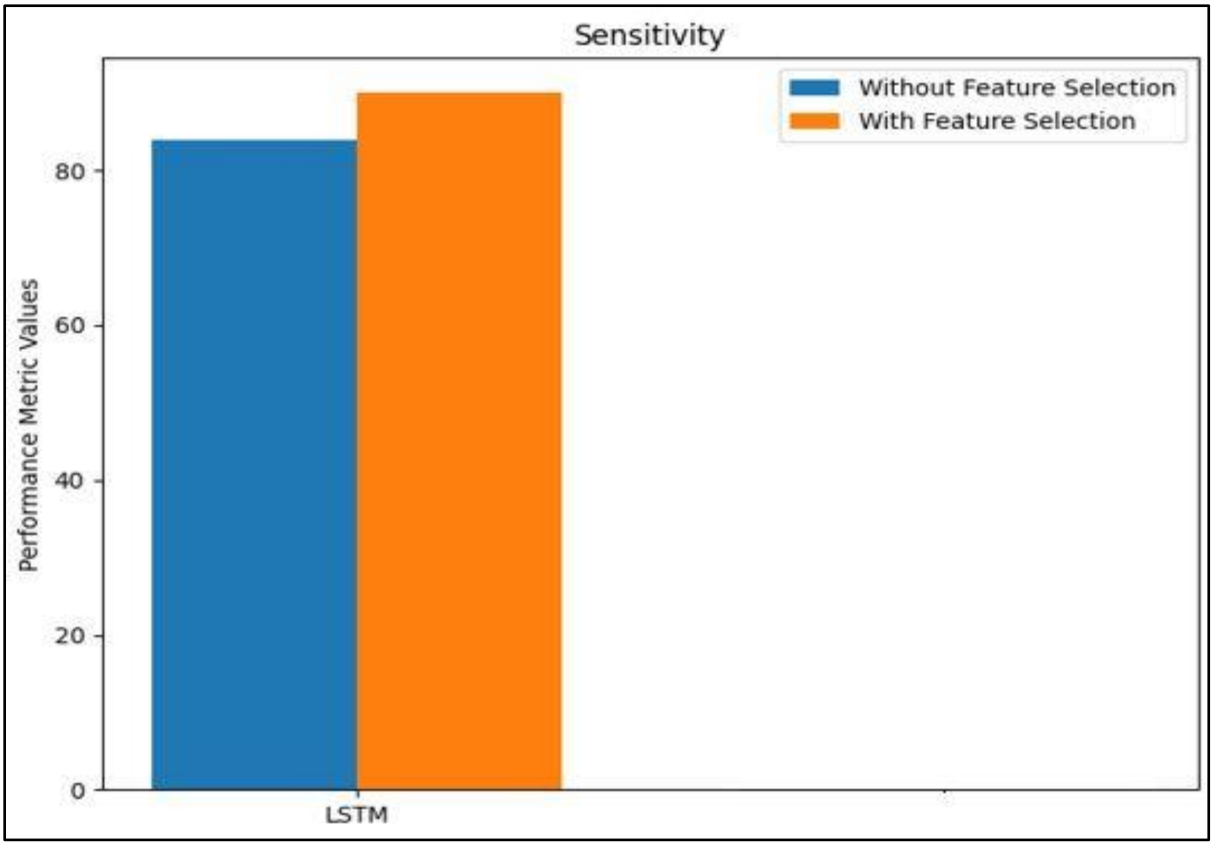

Figure (7): Sensitivity of LSTM Model
Source: Based on Python Outputs

Figure (7) illustrates the Sensitivity of the LSTM algorithm in learning and prediction (performance testing) processes in a general context. The blue column represents learning and prediction using all input variables, while the orange column represents reliance on specific values and a defined goal, utilizing the last column in the data, which represents the time delay.

From the above evaluation charts, we observe the high accuracy of the LSTM model in estimating the project duration. This signifies the robust predictive capabilities of the model in handling complex project dynamics. Such accurate estimations contribute to enhanced decision-making in project management, fostering efficient resource allocation and timely completion.

3.2.3 The Confusion Matrix:

The Confusion Matrix is an evaluation tool used to assess the performance of a classification model, such as neural networks, by comparing the actual classification of data with the classification given by the model. The matrix consists of four sections: cases that were correctly classified as positive (True Positive) and those correctly classified as negative (True Negative), in addition to cases that were wrongly classified as positive (False Positive) and those wrongly classified as negative (False Negative) (Gwet, 2001) and (Visa, et al, 2011), The figure (8) illustrates the outcome of the Confusion Matrix, the result of the Confusion Matrix from the model appeared as follows:

$$TP = 1987, FP = 221$$
$$FN = 144, TN = 1178$$

To extract accuracy, sensitivity, and recall rates, the calculations were performed according to the specific formulas as follows:

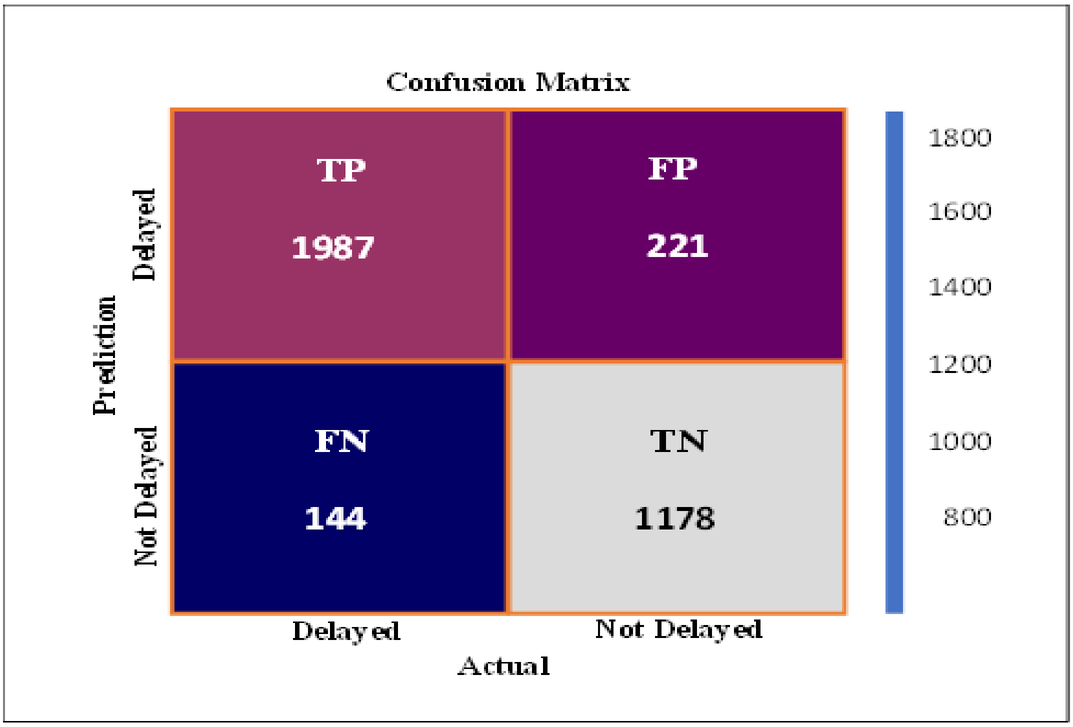

Figure (8): Confusion Matrix.
Source: Based on Python Outputs

1- Accuracy $= \frac{(TP + TN)}{(TP + TN + FP + FN)} \times 100\% \Rightarrow = \frac{1987 + 1178}{(1987 + 1178 + 221 + 144)} = 0.888 \approx 89\%$

2- Recall $= \frac{TP}{(TP + FN)} \times 100\% \Rightarrow = \frac{1987}{(1987 + 144)} = 0.932 \approx 93\%$

3- Specificity $= \frac{TN}{(TN + FP)} \times 100\% \Rightarrow = \frac{1178}{(1178 + 211)} = 0.841 \approx 84\%$

4- Positive Predictive Value $= \frac{TP}{(TP+ FP)} \times 100\% \Rightarrow = \frac{1987}{(1987 + 221)} = 0.899 \approx 89\%$

5- Negative Predictive Value $= \frac{TN}{(TN+ FN)} \times 100\% \Rightarrow = \frac{1178}{(1178+ 144)} = 0.891 \approx 89\%$

6- Negative Response Rate $= \frac{FN}{(TN+ FN)} \times 100\% \Rightarrow = \frac{144}{(1178+ 144)} = 0.108 \approx 10\%$

7- F-Score $= \frac{2 \times Precision \times Recall}{Precision + Recall} \times 100\% \Rightarrow$

$$Precision = \frac{TP}{TP + FP} \Rightarrow = \frac{1987}{(1987 + 221)} = 0.899$$

$$F\text{-}Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \times 100\% \Rightarrow = \frac{2 \times 0.899 \times 0.932}{0.899 + 0.932} = 0.915 \approx 91\%$$

Therefore, based on the resulting confusion matrix and the previous performance calculations, it can be concluded that the (LSTM) model achieved a good accuracy of up to 0.888, indicating its ability to classify data correctly with an approximate 89% accuracy rate. Additionally, it demonstrated a high recall of around 93% and a sensitivity close to 85%. These metrics reflect the model's strong capability to effectively handle both positive and negative cases in a balanced manner.

The specificity metric emerged with a value close to 0.841, indicating the ability to handle negative cases with acceptable accuracy. This is evident from the model's capability to successfully identify negative cases with a high true negative rate. On the other hand, the Positive Predictive Value, which approaches 0.899, indicates that the model predicts positive cases with acceptable accuracy. Additionally, the Negative Predictive Value, which is approximately 0.891, demonstrates the model's ability to reliably predict negative cases.

Finally, the simple F-Score coefficient of 0.915 reflects a well-balanced trade-off between precision and recall. This measure is important for assessing the model's performance in cases where there is an optimal balance between positive and negative instances. Here, it can be concluded that the model exhibits a strong capability to classify and predict various scenarios, making it a valuable tool for enhancing decision-making processes within the context of the relevant research.

3.3 Discussion:

This study aimed to evaluate the LSTM model for classifying construction projects as either completed on time or delayed. The LSTM model achieved outstanding performance with an accuracy of 89% and a recall rate of 93%. The model demonstrated high reliability in predicting delays, consistent with the findings of the study conducted by Cheng, et al. (2019). The LSTM model excelled in estimating the remaining time to completion (ESTC) carefully. Additionally, the NN-LSTM model proved to be more reliable than the innovative formula of Earned Value Management (EVM) and exhibited superior performance compared to other artificial intelligence prediction models.

Furthermore, the definition of "true delay" relies on the duration and frequency of delays, as well as the establishment of a time threshold. If more than 15% of the total project time is exceeded, it is considered a genuine delay. Therefore, the objective is to introduce a new logical variable called "Delayed" to apply the time threshold. This is affirmed by the accuracy of the results achieved by the neural network (89% LSTM) using deep learning. This indicates that the utilized model was capable of predicting project delay times with a very low error rate, underscoring the precision of neural networks in forecasting project delay times.

Moreover, there is significance in the size and cost of the planned project in predicting delays. This is highlighted by the weightings of the LSTM model, showing that larger and more costly projects are more susceptible to delays. This aligns with prior research that has identified a correlation between increased size and complexity and project delays.

Finally, it has been concluded that the LSTM network is suitable for predicting project delays in their early stages using initial time schedules and cost metrics. However, the model's performance could potentially improve with additional training data covering diverse projects.

4. Conclusions :

Based on the achieved results, the researchers arrived at the following conclusions:

1.The potential use of artificial intelligence (neural networks) in project management aims to expedite project completion.

2.This study demonstrated that LSTM networks performed exceptionally well in predicting construction project delays based on planned features, achieving an accuracy of 89% and a recall of 93%. This underscores their effectiveness.

3.The main objectives of evaluating the LSTM model were successfully achieved.

4.Predicting delay times enables organizations, engineers, and contractors to leverage these techniques for improved project planning and more efficient schedule management.

5.Employing advanced technology like neural networks enables the early anticipation of potential issues and the implementation of strategies to mitigate their impact on schedules.

6.The use of artificial intelligence in project management is poised to enhance project team effectiveness.

7.Artificial intelligence contributes to forming insights about the environment and making informed decisions.

8.Applications of artificial intelligence are spreading across various fields, including project management.

9.Artificial intelligence in project management supports numerous initiatives and aids in managing diverse projects.

10. Project managers benefit from artificial intelligence by streamlining daily tasks and increasing productivity.

Authors Declaration:

Conflicts of Interest: None

-We Hereby Confirm That All The Figures and Tables In The Manuscript Are Mine and Ours. Besides, The Figures and Images, Which are Not Mine, Have Been Permitted Republication and Attached to The Manuscript.

- Ethical Clearance: The Research Was Approved By The Local Ethical Committee in The University.

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دور تقنيات الذكاء الاصطناعي في تعزيز سرعة إنجاز المشروع: دراسة حول استخدام شبكات LSTM للتنبؤ بأوقات التأخير

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مستخلص البحث

هدفت هذه الدراسة إلى البحث عن آليات لتحسين وتعزيز سرعة انجاز المشاريع من خلال تطبيق تقنيات الذكاء الاصطناعي. إذ اعتمدت الدراسة على منهج "استخدام شبكات LSTM للتنبؤ بأوقات تأخير المشروع"، واعتمد الباحثان على بيانات (3530) وحدة سكنية من أجل التدريب والاختبار والتنبؤ. ومن اهم أسباب اختيار أوقات التأخير كونها تشكل عائق كبير امام انجاز المشاريع الحيوية. وتتجلى مشكلة البحث في السؤال الرئيسي "هل يمكن استخدام شبكات LSTM بنجاح للتنبؤ بأوقات تأخير المشروع؟". وتكمن أهمية البحث في استخدام تقنيات الشبكات العصبية الطويلة القصيرة المدى (LSTM) لتحسين التنبؤ بأوقات تأخير المشاريع، مما يساهم في تحسين تخطيط وإدارة المشروعات، وتقليل التأخير وزيادة الكفاءة في تنفيذها. ومن بين أهم النتائج التي توصلت اليها الدراسة هي استخدام الشبكات العصبية الطويلة القصيرة المدى (LSTM) يمكن أن يحسن التنبؤ بأوقات تأخير المشروعات الإنشائية بشكل فعّال، إذ انها أظهرت دقة مرتفعة ونسبة استرجاع عالية. وان تقديم هذه التقنية المتقدمة لإدارة المشاريع يمكن أن يؤدي إلى تحسين جداول العمل وتخطيطها وتقليل التأخيرات، مما يساهم في تحسين كفاءة وإنتاجية العمل واتخاذ القرارات الاستراتيجية بشكل أكثر دقة.

نوع البحث: ورقة بحثية

الكلمات الرئيسة: الذكاء الاصطناعي (AI)، تعلم الآلة (ML)، التعلم العميق (DL)، الشبكات العصبية الاصطناعية (ANN)، شبكة LSTM، إدارة المشاريع (PM)، أوقات التأخير (DT).

***البحث مستل من رسالة ماجستير**