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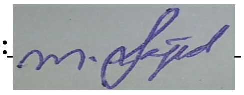
Signature: 

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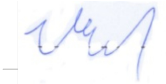
Signature (HOD): 

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We hereby recommend that the dissertation prepared under our supervision by: Muhammad Usama (00000330049) Titled: Forecasting Urban water demand and supply using machine learning models be accepted in partial fulfillment of the requirements for the award of MS in Robotics & Intelligent Machine Engineering degree.

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AUGUST 2023

Declaration

I certify that this research work titled "*Forecasting Groundwater Consumption for an Urban Environment Using Machine Learning Techniques"* is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources has been properly acknowledged/referred.

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Copyright Statement

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Abstract

Poor water management systems in major cities can be addressed by water consumption forecasting using multiple factors e.g., climatic data, population count, and water requirement. In this study, a primary dataset is obtained including water consumption of a 3 sq. kilometres urban site in Pakistan over the course of 7 years along with environmental variables like temperature, precipitation, humidity, wind speed, and population. The results indicate that time-series modelling is the best approach for forecasting problems that include environmental variables like temperature, precipitation, humidity, wind speed, population, and water consumption. Three distinct machine learning models, namely artificial neural network, Long Short-Term Memory (LSTM) models, and transformers, were rigorously evaluated. In terms of accurately forecasting urban water demand and supply, the proposed architectural framework of transformer models outperformed the other models, according to the evaluation results. The LSTM model has an R2 score of 0.31 for predicting monthly water consumption, whereas the transformer performed exceptionally well with an R2 score of 0.98. For further substantiation, annual water consumption forecasts are made for the transformer whose R2 score was 0.917. The proposed model has been successfully employed to forecast water consumption in all four seasons indicating that it is impactful for sustainable water resource management in an urban environment.

Key Words: *Water Management, Urban Water Consumption, Forecasting, Time-Series Analysis, Machine Learning*

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CHAPTER 1: INTRODUCTION

Due to the rapid increase in population across the globe during the last few decades, water sustainability in an urban environment is further aggravated due to the uncertainties such as demography and weak municipal management (Albert et al., 2021; Lumborg et al., 2021). The water scarcity issue is one of the key target areas that need to be addressed to overcome this threatening situation considering that around 2.2 billion people globally do not have access to safe water(Van Vliet et al., 2021). The diverse water systems such as lakes, rivers, and aquifers that keep the ecosystem alive are overutilized and are being drained at a rapid pace. By 2025, 65 per cent of the world's population may face water scarcity(Karandish et al., 2021) which indicates that there is an immediate need for effective water management solutions to address this precarious situation (Kajewska-Szkudlarek & Łyczko, 2021; Parris, 2011).

The exponential increase in urban population has placed an extraordinary strain on water supplies, raising concerns about its long-term sustainability at a time when the quality of accessible water resources is being degraded by anthropogenic activities. Globally, cities are exhausting their water reserves because the extraction rate far exceeds the recharge rate from precipitation(Ahmadi et al., 2020). Urban water balance in cities is a big challenge in Low- and Middle-Income Countries (LMICs) such as Pakistan, as the water recharge process is different in cities than in rural areas and is aggravated by factors like unauthorized extraction of water outside municipal control. Water consumption per capita in Pakistan varies from 30L to 350L per day depending on the region, however, water quality and quantity are compromised for most of the inhabitants. Moreover, water consumption is also affected by the changes in the hydrological cycle due to urbanization (Chowdhury & Behera, 2022; Wakode et al., 2018). Therefore, it is important to consider the impact of urbanization and population increase on the demand and consumption of water and forecast its effect (Khan et al., 2021). Special attention has been paid to agricultural escalation to overcome food insecurity issues, but limited work has been done to manage water resources efficiently in urban areas. It has been reported in the literature (Di Mauro et al., 2021) that mid-size cities require purpose-built innovative tools to apply the water resilience concept in the face of climate change. Due to the lack of accountability for water usage and poor water management system (WMS) at the domestic level, the wastage of water in urban buildings has been significantly increasing. It is vital to work on water consumption modelling to

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formulate the factors determining the water demand and its sustainable usage in urban areas.

The National University of Sciences and Technology is one of the leading universities in Pakistan. It is located in Islamabad, the capital of Pakistan. NUST is in sector H-12 and covers an area of almost 3 sq kilometres. It has a population of more than 5000 individuals. Being so large and populated university, there is a large demand for water. The water transportation system within the NUST was designed by NESPAK (National Engineering Service Pakistan). The construction and management (C&M) department controls the distribution of water. The C&M department works under the project management office PMO. In Islamabad, water distribution is controlled by the Capital development authority CDA. During the construction of NUST, water was supplied by the CDA through the pipelines drawn from CDA reservoirs to NUST. But later on, they failed to supply the water and thus the water supply became a problem. In order to tackle that problem NUST built their own water supply system. They bored wells at different positions, built overhead tanks for storage and made a system of pipelines and distribution. Thus, a water distribution system was developed. With the passage of time, the population has increased and so the consumption of water has also increased. With this increment, there occurred a gap between supply and demand. Now the water problem is a major crisis in the world and it especially hit Pakistan problem is becoming worse day by day. Thus, we have only considered Islamabad and specifically the NUST for this research. So, this project is conducted in order to regulate water distribution in NUST. We have collected different types of data and made predictive analyses. Different departments and resources provide the data. The data has various parameters like temperature, population etc. This data is further arranged in a tabular form in order to have the proper presentation of data. This data is for the previous seven years. Then we applied machine learning techniques for the modelling of our data.

For Real-Time Control (RTC), water demand estimation is an essential factor for proactive management (Boyd et al., 2019). Prediction of water consumption is a complicated problem when dynamic time series and irregular anthropogenic influences are involved but several research studies have been employing machine learning techniques for water modelling and its management (Mouatadid & Adamowski, 2017). As water consumption forecasting is strongly affected by the model structure and input variables, therefore, necessitating the development of suitable prediction models is an important research problem and is the subject of this research thesis.

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The ground truth data is used by statistical and machine learning techniques to identify trends and patterns. Auto-regression (AR), autoregressive moving average (ARMA), and autoregressive integrated moving average (ARIMA) are three common types of approaches. In order to model time-series data, deep learning techniques based on convolutional and recurrent neural networks have also been created. These sequence-aligned models are obvious options for time series data modelling. However, these techniques have difficulties in modelling long-term and complicated linkages in the sequence data because of "gradient vanishing and exploding" issues with RNNs and the constraints of convolutional filters (Wu et al., 2020).

In this thesis, we created an urban water management system using a novel time series forecasting technique based on transformer architecture (Vaswani et al., 2017). The transformer does not process input in an ordered sequence, in contrast to sequence-aligned models. Instead, it analyzes the complete sequence of data and uses self-attentional mechanisms to understand how the data are interconnected. As a result, transformer-based models have the ability to describe time series data with complicated dynamics that are difficult for sequence models to handle.

1.1 Thesis outline

Chapter 1 provides a concise introduction, outlining the research's primary objectives. Chapter 2 delves into a comprehensive literature review, illuminating the challenges posed by the water crisis and its current state. Various methodologies utilized in past predictive approaches are also explored. In Chapter 3, a thorough exploration of the employed methodologies is presented, accompanied by detailed formulations. This section also offers an intricate breakdown of the NUST water plan. Moving on to Chapter 4, a meticulous account of the software-based experimentation is provided. Elaborate detailing of the parameters and conditions utilized is also included. Chapter 5 showcases the research outcomes, concluding remarks, and an in-depth discourse. The conclusion is followed by an examination of the applications and prospective suggestions for the future.

CHAPTER 2: LITERATURE REVIEW

Various applications have employed data-driven techniques, including wastewater management (Boyd et al., 2019), water availability assessment and water demand forecasting (Mouatadid & Adamowski, 2017; Seo et al., 2018). Among these techniques, deep learning

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models have emerged as a prominent approach in hydrological modelling over the past few years. For instance, Cutore et al. (Cutore et al., 2008) used shuffled complex evolution metropolis algorithms integrated with an ANN to forecast daily water consumption and applied them to the city of Catania, Italy as a case study. However, in this study, the effect of climatic parameters on daily water consumption was not considered. Zubaidi et al. (Zubaidi et al., 2020) analyzed the water consumption data of Baghdad city by using a signal pre-processing approach to extract stochastic signal data without considering spatial and climatic data to analyze urban water demand forecasting. Another case study was performed on a province and financial hub in South Africa, Gauteng, by using ANN optimized with back search algorithms (BSA-ANN). They concluded that the hybrid models can be more precise and reliable to predict water demand. None of the research cited above considered the impact of climate change and population growth, leading to deficient water forecasting models with high uncertainties, which motivates researchers to further improve their AI models.

Similarly, Kuo-lin Hsu et al. (Hsu et al., 1995) used a three-layered Artificial Neural Network (ANN) to forecast the rain runoff model. They introduced a linear least-squares simplex method to identify the structure, parameters, and potential of the ANN model to simulate the nonlinear hydrologic behaviour of watersheds. However, their model does not provide physically realistic components and parameters while Raman et al. (Raman & Sunilkumar, 1995) used data-driven Multivariate Auto-Regressive Moving Average (ARMA) time series models for the synthesis of monthly inflows record of water reservoir. In this research, the nonlinear ANNs model approach is shown to give better results for water reservoir inflows. Coulibaly et al. (Coulibaly et al., 2001) and Jain et. al (Jain & Ormsbee, 2002) also calibrated three different ANNs models using hydrometeorological data and short-term water consumption records to model water table fluctuation in the Gondo aquifer by using an existing water supply system to forecast short term water demand using regression and time series analysis. The research concluded that in selected sites, water demand is highly correlated with rainfall occurrence rather than the amount of rainfall and the short-term the water demand process is a dynamic process that mainly depends upon air temperature. Nayak et. al (Nayak et al., 2006) investigated the potential of ANNs to forecast the fluctuation of water consumption of two under-observation wells at the unconfined coastal aquifer of India. Their model can forecast the water level for up to four months and is used to plan the ground and surface water of coastal areas to maintain the

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natural water table gradient. It is worth noting that the studies mentioned were conducted at a time when Artificial Neural Networks (ANNs) were not as extensively developed and lacked the advancements seen in modern hardware, such as powerful graphics processing units (GPUs). However, despite these limitations, the studies still offer valuable insights and make significant contributions to their respective fields.

Some researchers have explored the development of hybrid Artificial Neural Networks (ANNs) and their application in the development of water management systems. For instance, Gaur et. al\cite{gaur2018application} used simulation optimization to solve water resource management problems. ANN and Bagged Decision Trees models (BDT) along with Particle Swarm Optimization (PSO) were trained and used as an approximator of water modelling based on the Analytic Element Method. The water flow model was developed using these coupled PSO-ANN and PSO-BDT models and applied to estimate the optimal design and cost of a well-defined system. For the designing of the well-field management system, using this approach it is compulsory to provide a piping network and simulation-optimization model. Lee et. al (Lee et al., 2019) and Kadam et. al (Kadam et al., 2019) proposed the ANN technique in which input parameters include one natural and two anthropogenic factors by using the ANN model to predict the quality of drinking water in the Shiv Ganga River basin. Thirty-four samples were collected and analyzed for cations and anions during pre- and post-monsoon season. Salem et. al (Salem et al., 2019) used WetSpass-M based on a geographic information system for the assessment of the spatial and seasonal distribution of water recharge. Gonçalves et. al (Gonçalves et al., 2020) constructed a three-dimensional finite element model to assess the flow dynamics and water recharge. Their results show that the selected site's current recharge rate is far less than the previous estimates which is an alarming situation for water resource management while Khoshand A.(Khoshand, 2021) used one year of data of water consumption for sustainable water management with the help of time-delay neural networks.

In another research by M. Ebrahim. et al.(Banihabib & Mousavi-Mirkalaei, 2019) , two forecasting models were proposed for urban water consumption in an arid region i.e., extended Auto-Regressive Integrated Moving Average (ARIMA) and Nonlinear Auto-Regressive Exogenous (NARX) methods. Their study is centered on the arid regions using linear and nonlinear models to check the reliance of new forecasters i.e., sunny hours and population.

The most recent research, a deep learning-based prediction framework carefully analyzes real-world time series data and displays very precise prediction outcomes. In order to provide appropriate prediction outcomes, forecasting models using artificial neural networks particularly learn different patterns and characteristics that traditional machine-learning algorithms and regression models cannot grasp (Li & Fu, 2023). For instance, Kim et al. introduce a transformer model-CNN multivariate time series prediction framework that captures temporal characteristics and variable correlations. The suggested approach beats earlier forecasting models by 3 to 5 per cent in predicting time series data with cyclic patterns and strong variable correlation by introducing a hybrid transformer-CNN approach to overcome time series prediction model limitations (Kim & Kim, 2022). Similarly, transformer-based architectures have also gained notable attention in time series analysis of machines' life estimation and predictive modelling \cite{wahid2023self}. Furthermore, researchers also explored their application in anomaly detection of sensor data and wireless systems (Kumar et al., 2023; Wang et al., 2023).

This research study undertakes a comprehensive comparative analysis focused on transformer-based time-series models, with the primary objective of accurately estimating water consumption within a specific humid subtropical region. A distinctive aspect of this study lies in its utilization of a novel dataset, meticulously compiled by the authors themselves, which is intended to be openly shared with the wider research community. This dataset represents a valuable contribution to the field, as it offers researchers a new resource to further their investigations and analyses. The central focal point of this investigation is the juxtaposition of the performance of transformer-based models against that of conventional recurrent neural networks (RNNs) and other neural network models. By doing so, the study aims to gauge the efficacy and potential of transformer architectures when dealing with the intricate dynamics of water consumption patterns over time.

The outcomes of this study underscore the transformer architecture's superiority in capturing long-term dependencies and subtle temporal patterns inherent in water consumption data. While conventional neural network models and RNNs are designed to learn sequential patterns, the transformer architecture's innovative attention mechanisms allow it to more effectively capture relationships across extended temporal spans, a trait highly relevant to the intricacies of water consumption behavior.

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The results of the analysis not only highlight the transformer model's ability to enhance accuracy in estimating water consumption but also suggest its broader utility in similar time-series prediction tasks. This establishes a promising precedent for the application of transformer-based models in forecasting scenarios where temporal patterns play a crucial role. An integral aspect of this research's significance is the accessibility of the unique dataset. By providing this dataset to the research community, the authors foster collaboration and encourage further investigations in the realm of water resource management. Furthermore, the dataset's specificity to a humid subtropical region allows for the exploration of similar geographical contexts, potentially providing insights into water consumption behaviors in analogous climates.

In conclusion, this research study stands as a noteworthy contribution to both the field of time-series modeling and water resource management. Through its comprehensive comparison of transformer-based models to conventional neural network counterparts, it not only showcases the advantages of transformers in capturing complex temporal patterns but also facilitates future investigations and applications in water resource management for regions with similar climatic conditions.

Table 1: Climate data used as variables in model training

Date	Population (Person)	Ambient Temperature(C^0)	Dew Point Avg Temp (C^0)	Humidity %	Precipitation (Inch)	Ground water Consumption (m^3/day)
Year 1						
01 Jan	2892	11.11	1.11	57.5	0	1824.6
02 Jan	3554	11.66	2.22	59	0	1883.8
03 Jan	3554	12.22	3.34	66	0	1802.2
04 Jan	3554	11.77	3.88	66	0	1810.4
.	.	.	.	.	.	.
.	.	.	.	.	.	.
Year 4						
01 Jun	4088	27.77	12.77	33.5	0.2	1493.1
02 Jun	4088	28.88	13.34	42.5	0	1537.5
03 Jun	4087	26.21	14.15	47.5	0	1481.8
.	.	.	.	.	.	.
.	.	.	.	.	.	.
Year 7						
01 Dec	3484	10	0.55	53.5	0.67	1651.3
02 Dec	3484	11.66	3.88	57.5	0	1653.5
03 Dec	4469	10.55	3.33	59.5	0	1679.6

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CHAPTER 3: METHODOLOGY

3.1 Area of Study

The present study focused on a humid subtropical climatic region located in Islamabad, Pakistan, at 33.64^o N 72.98^o E and 500m above sea level on the Pothohar Plateau. The climatic conditions of this region are characterized by hot summers in June and cold winters in January, while the monsoon season occurs from the end of June to the end of September with a total average rainfall of 31.13 inches (Aslam et al., 2021). The reason for choosing this region is that it is facing severe water shortage issues for the last two decades due to climate variability and increasing population(Abbasi, 2021; Mehmood, 2021). The environment of the selected site is diverse including urban forest, natural lake, residential areas, offices, sports complex, and markets spread over an area of almost 3 km^2 as shown in Figure 1.

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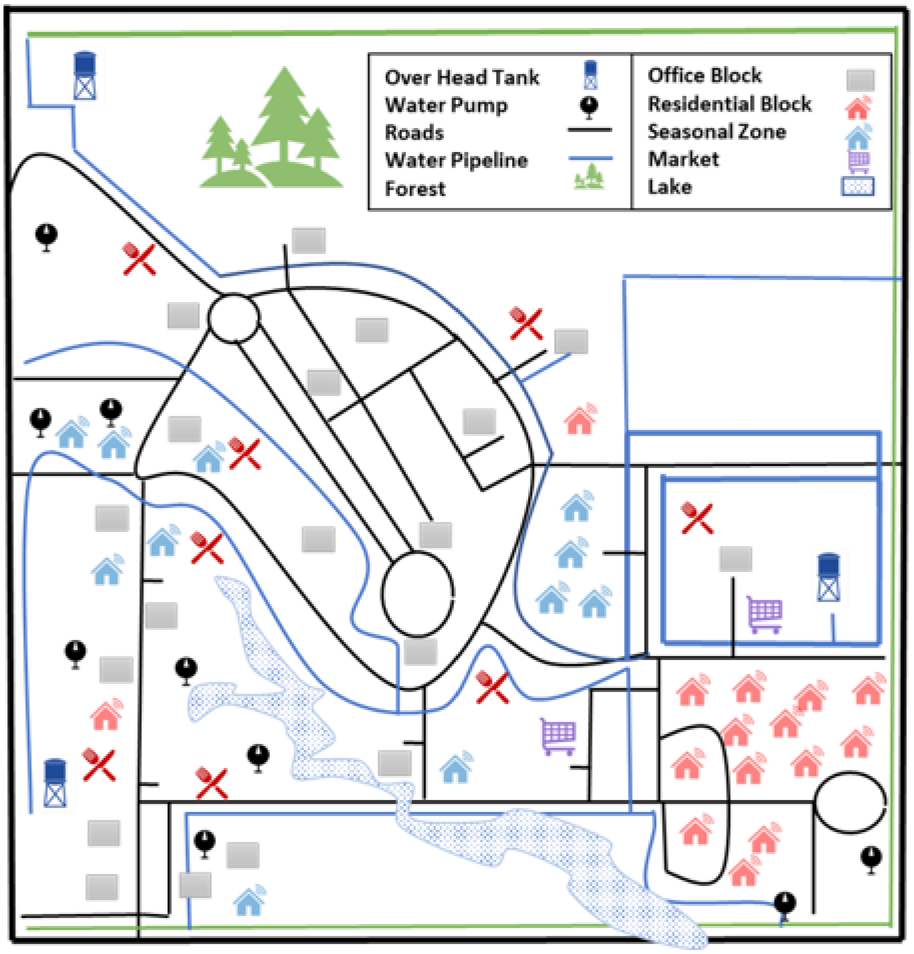

Figure 1: Map of 287 Hectare (3 sq km) site showing offices, residential zones, markets, restaurants, wells etc.

3.2 Dataset Description

In this study, seven years of water consumption data, as well as population data, has been collected manually with the help of the local municipality office and coupled with climatic data, for modelling the proposed machine learning algorithm. The weather data was recorded for 7 years using precise meteorological instruments installed in Islamabad at 33.64o N 72.98o E and 500m above sea level. Instruments used to record weather parameters are detailed in Table 2.

The novel training data set has seven variables with daily information on population count, water consumption in cubic meters, ambient temperature, dewpoint temperature, percentage humidity, wind speed, and precipitation in inches for seven years. Our dataset provides information regarding the local population of selected sites and water consumption that was not previously curated. The population data is categorized into two sub-groups i.e.,

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permanent residents and seasonal residents. Permanent residents live in residential areas throughout the year while seasonal residents live 8-10 months yearly. The urban site selected for water consumption in this research comprised of three overhead tanks (OHTs) which are filled with nine different water pumps installed at distant locations as shown in Fig. 1. The collected data is analyzed for research using standard validation techniques for predicting water consumption and availability over the coming years. The collected data is then pre-processed by performing data imputation to check null or missing values. After this, the dataset is split into training and validation sets for training machine learning models, and at the end proposed model is evaluated based on different error metrics using test data sets.

In multivariate time-series datasets, there are some features whose contribution in forecasting target value is high, but some features contribute very less or even can worse the model performance if included. For our dataset, features were selected based on the performance of the Pearson Correlation test. All selected features have a high correlation with the target variable while features with a high correlation with each other and a negative correlation with the target variable were not considered. Based on this, after performing data analysis, 5 features were selected as detailed in Table 1. The flow chart of the overall methodology is illustrated in Figure 2.

Table 2: Detail of Instruments used for weather data collection.

Variable	**Instrument**	**Range**	**Resolution/Sensitivity**
Ambient Temperature in C	Campbell CS215	-40 to +70 ^{o}C	0.001 ^{o}C
Relative Humidity (RH)	Campbell CS215	0-100% RH (-20^{o} to +60^{o}C)	0.03% RH
Wind Speed in m/s	NRG 40H Anemometer	1 m/s TO 96m/s	0.78m/s
Barometric Pressure	Campbell CS100	600 to 1100 hPa	0.01 hPa

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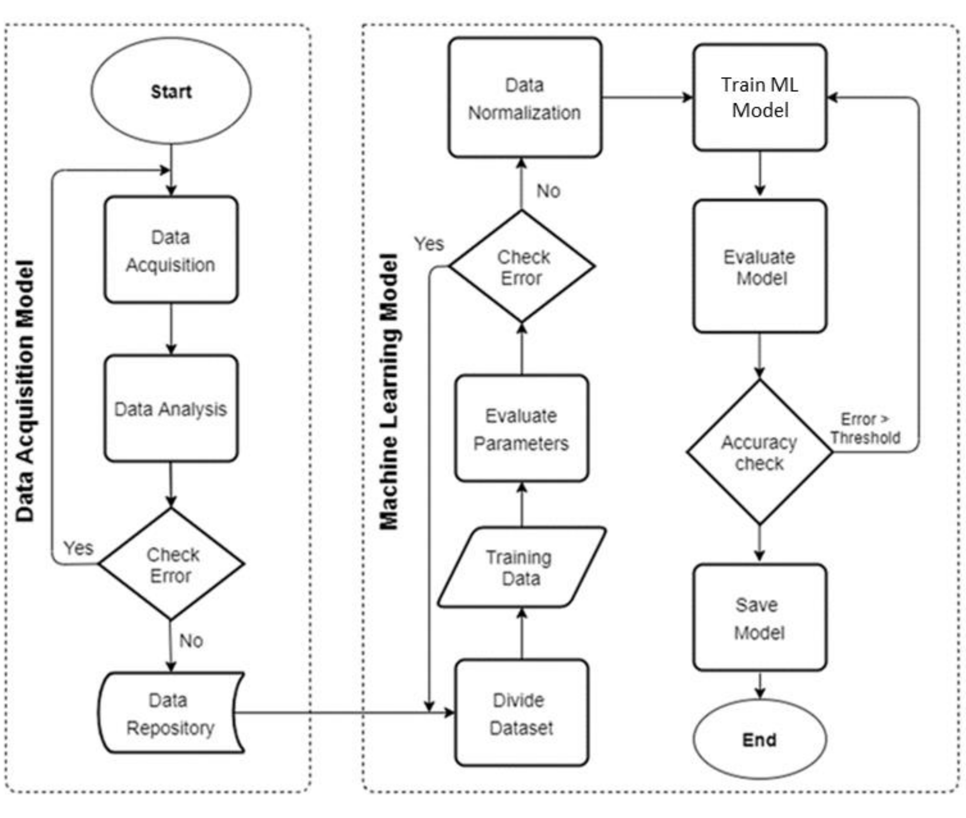

Figure 2: Flow chart of the methodology for the reported study

3.3 Tested Models

3.3.1 Artificial Neural Networks(ANN)

One of the most ingenious systems created for machine learning is an Artificial Neural Network (ANN) that simulates the human brain in information processing and has the ability to teach itself to solve problems. ANNs composed of three main units namely Input, Hidden, and Output layers. Hidden layers are responsible for processing and enable model to learn the data patterns. The neurons in hidden layers are the base processing units which take data from input layer and learn depending on the type of chosen learning method and forward the result to the final output layer. A simple architecture of Artificial Intelligence is given in Figure 3.

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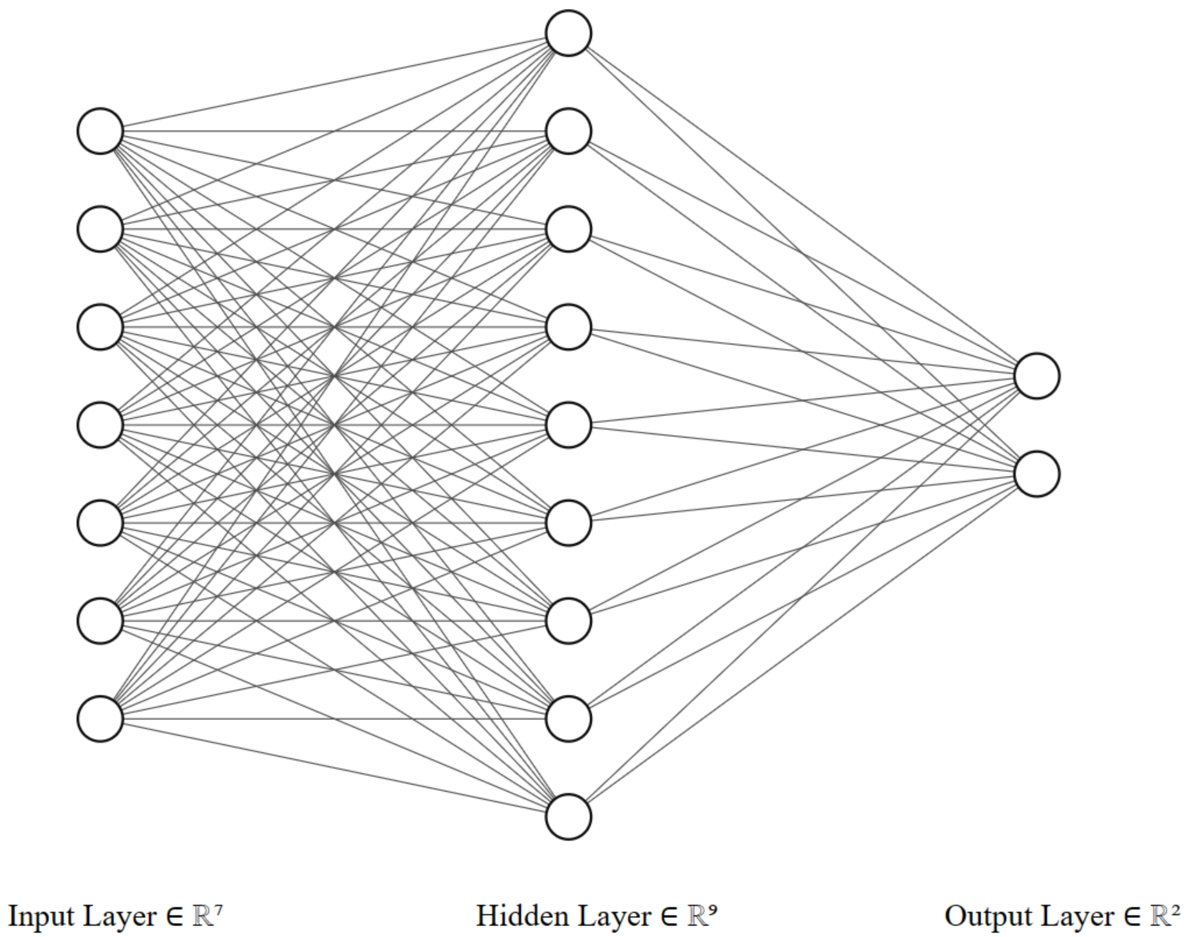

Figure 3: Architecture of Simple Artificial Neural Network

Using various architectures and hyperparameters, different deep neural network (DNNs) models were trained. Figure 4 shows the relationship between the accuracy of models with learning rates ranging from 0.01 to 0.05. Model-1 consists of 4 hidden layers which have 64, 32, 16, and 3 neurons respectively. The first three layers of this model have the Relu activation function while the last one has Softmax and Stochastic Gradient Descent optimizer. Model-2 also consists of 4 hidden layers which have 32, 16, 10, and 3 neurons respectively with different momentum but the same activation function and optimizer as in the previous model. The remaining two models (model-3 and model-4) have different activation functions and optimizers but none of the above models has the accuracy of more than 70%.

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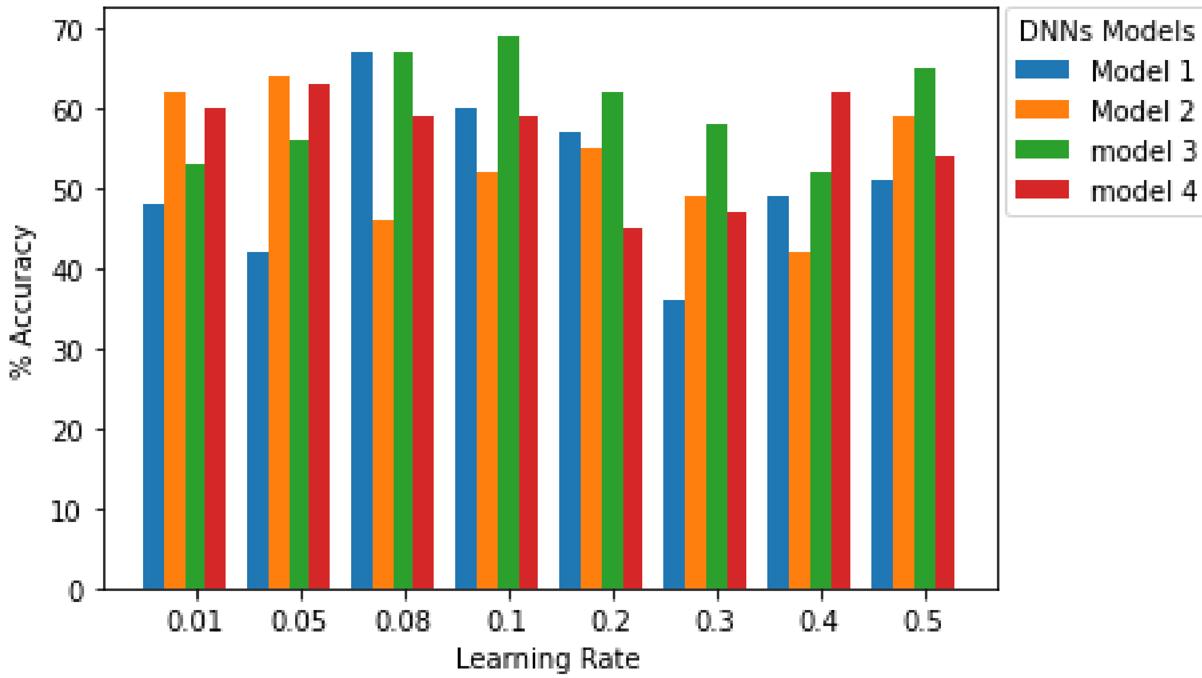

Figure 4: Accuracy plots for different machine learning models using varying learning rates.

3.3.2 Convolutional Neural Networks (CNN)

Convolution Neural Network (CNN) is a type of Neural Network designed primarily for pattern recognition in images. It is widely used for Object Detection, Image Classification, Face Recognition, Object Recognition, Object Classification, etc. CNN is typically employed in Computer Vision problems in which data consists of images passing through a series of convolutional layers with filters called Kernels, Fully Connected (FC) Layers, Pooling Layers, and various optimization functions that classify objects with probabilities between 0 and 1. Since images consist of large matrices with high dimensions, the use of CNN provides an advantage by reducing the number of modelling parameters.

In addition to their use in computer vision and image pattern recognition problems, CNN can also be used for time series forecasting by adjusting the input dataset's dimension. Figure 5 demonstrates the example of CNN architecture.

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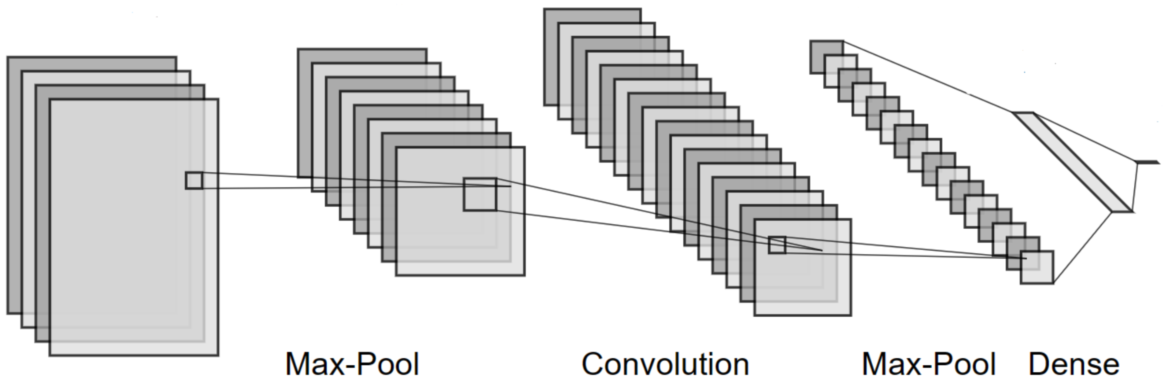

Figure 5: Example of Convolutional Neural Network Architecture

3.3.3 Long Short Term Memory (LSTM)

Long Short-Term Memory (LSTM) represents a significant advancement over the conventional Recurrent Neural Network (RNN) architecture. In recent years, RNNs have garnered notable achievements in various domains, including language modeling, translation, speech recognition, and image captioning. The key attribute of RNNs is their ability to handle sequential data, such as time series, by virtue of the recurrent loops within their processing units. These loops contribute to information retention and processing units that are intricately connected to the sequential nature of the data they operate on. However, despite RNNs' successes, they encountered limitations in managing long-range dependencies, hampering their effectiveness in scenarios requiring extensive memory retention. This limitation led to the emergence of Long Short-Term Memory (LSTM) networks as an extension of the RNN paradigm. LSTMs were designed to address the deficiency of RNNs in capturing and preserving long-term relationships within sequential data.

The primary differentiating factor between LSTMs and RNNs lies in the architecture's complexity and depth. LSTMs comprise four distinct neural network layers, each playing a specialized role in the overall process, as opposed to RNNs, which are typically composed of a single layer. This enhanced structural complexity allows LSTMs to effectively capture and utilize contextual information over extended sequences.

To provide a visual representation, Figure 6 illustrates a simple diagram of an LSTM network. This diagram serves to depict the various components and connections within the

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LSTM architecture, showcasing its unique structure designed to overcome the challenges of handling long-range dependencies. In essence, the introduction of LSTM networks serves as a pivotal advancement in the realm of sequential data processing. By incorporating multiple specialized layers, LSTMs empower neural networks to retain and exploit contextual information across extended sequences, effectively addressing the limitations that hindered RNNs in managing long-term dependencies.

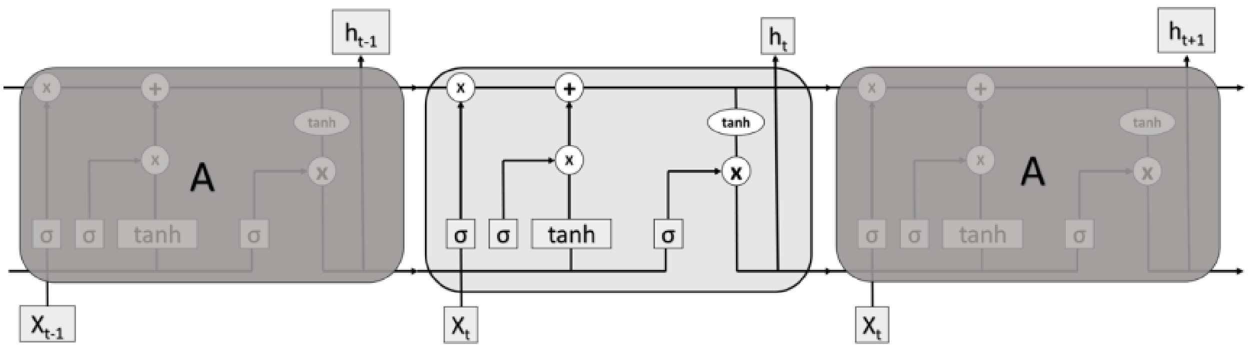

Figure 6: LSTM module having 4 NN layers

3.3.4 The Transformer

In the domain of deep learning applications, transformers emerge as a distinctive category of artificial neural network architecture tailored to tackle the intricate task of translating or transforming input sequences into corresponding output sequences. This architecture, known as the "transformer," is specifically designed to overcome challenges related to sequence manipulation. Central to the transformer's design is its reliance on self-attention mechanisms. The transformer architecture consists of a series of stacked blocks, each encompassing a set of crucial components. These components include feed-forward layers, layer normalization, self-attention mechanisms, residual connections, and attention scaling.

The self-attention mechanism within the transformer is particularly noteworthy. It empowers the model to weigh the significance of different elements within the input sequence in a dynamic and context-aware manner. This capability to focus on various parts of the input sequence to differing degrees ensures that the model can effectively capture intricate relationships and dependencies present within the data.

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The stacked blocks within the transformer architecture allow for the gradual extraction and transformation of information as it traverses through the layers. By incorporating feed-forward layers, the model gains the ability to process and reshape the data, facilitating the translation or transformation process. Layer normalization ensures stable and consistent computations, contributing to the stability of the model's training and overall performance. The concept of residual connections is integral to maintaining the flow of information within the architecture. These connections facilitate the unobstructed passage of data through the layers, minimizing the risk of information degradation or loss as it progresses through the network.

Furthermore, attention scaling plays a pivotal role in regulating the impact of self-attention. It ensures that the magnitudes of attention scores are appropriately scaled, preventing potential issues related to excessively strong or weak attentiveness to certain elements in the input sequence. In summary, the transformer architecture represents a revolutionary approach in deep learning applications, excelling at handling the translation or transformation of input sequences into output sequences. Its innovative utilization of self-attention mechanisms, coupled with the interconnected components of feed-forward layers, layer normalization, residual connections, and attention scaling, collectively contributes to its remarkable ability to capture complex dependencies and relationships within data sequences.

The transformer consists of two blocks, an encoder and a decoder. A Transformer Encoder accepts a singular sequence and does not perform any subsequent masking. It then applies a stack of independently parameterized, each consisting of (1) multi-head attention and (2) feed-forward. Thus, the output of each Block serves as the input for the subsequent Block. The decoder is used to future mask each application of self-attention (Shaw et al., 2018). This makes sure that the informational constraints are constant throughout the architecture.

In proposed model, to effectively capture temporal dependencies, the model employs multiple stacked Transformer Encoder blocks, each of which consists of attention mechanisms and feed-forward layers. Encoder blocks make use of residual connections to facilitate gradient propagation and improve training stability. The outputs of the Encoder blocks are collected using global average pooling, which facilitates the extraction of high-level features. A Multi-Layer Perceptron (MLP) layer performs additional processing on the consolidated data. The final output layer is a dense regression layer that predicts the future values of water consumption.

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CHAPTER 4: NUST WATER PLAN

In this chapter NUST water plan will be discussed in detail. As discussed earlier in introduction that water plan was designed by NESPAK. Under this plan, several bores of water are drilled, and several overhead tanks are made. The water plan is shown in the figure 7.

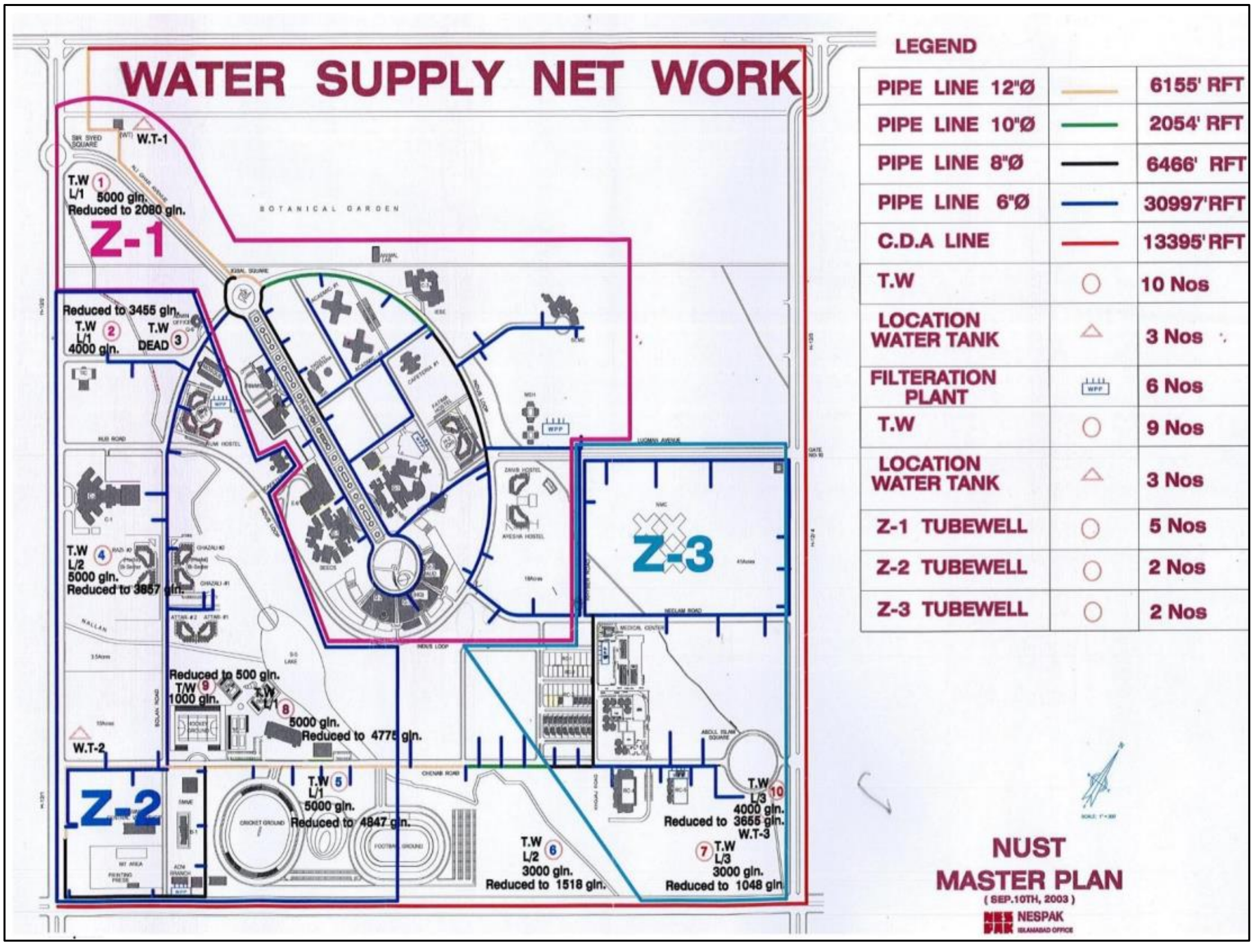

Figure 7 NUST Water Plan

4.1 Zonal Division of Water

The university is divided into three zones Z1, Z2, Z3. This division is indigenous part of Plan and is done in order to aid the distribution and make flow accessible to each building.

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4.1.1 **Zone 1**:

The areas that are included in zone 1 are as follows as Central library, NUST main office, CIPS, SEECS, NBS, RIMMS, SADA, IGIS, IESE, Concordia 1 & 3, Faculty Café, SCME, Iqra apartments. The girls' hostels are also included in this zone. They are Ayesha, Zainab, Khadija, Fatima-1 and Fatima-2. This zone has pump /tube well no 01 and 02 and has over head water storage tank 01. Both of these pumps provide the water to OHT 01.

4.1.2 Zone 2:

This zone has very diverged layout. The pumps/ tube well located in this region are 2, 4 5, 6 and 8 and has storage/ overhead tank 02. It has also an aquifer or lake. This area is further divided into two sub areas Area 2A and 2B.

4.1.2.1 Area 2A

The buildings/ sites located in this area are SMME, SNS, MDDC, PMO, NUST press, NG staff quarter and Masjid Noor. This area is provided water by OHT 2 and pump 4 and provides water to this tank.

4.1.2.2 Area 2B

The sited located in area 2b are Bahttai faculty mess, NIT, NICE, UPCASE, CIE, admin directorate, HBL, Concordia 2, all hostels of Rumi , Ghazali and Attar. Most of water is supplied through OHT 2 Which is filled by 5 and 8 pump in this area. Some direct lines also connected from 5 and 8 pump to boys' hostels. Overhead tank 2 has 4050 m3 capacity.

4.1.3 Zone 3

The main building in this zone are Medical Centre, Residential Apartments and Masjid Taqwa. This zone contains water tube well No. 7 and 10, and water storage tank overhead tank 3. Tube wells directs water to OHT 3 from where residential blocks are fulfill their need. All of this arrangement can be given in figure 8.

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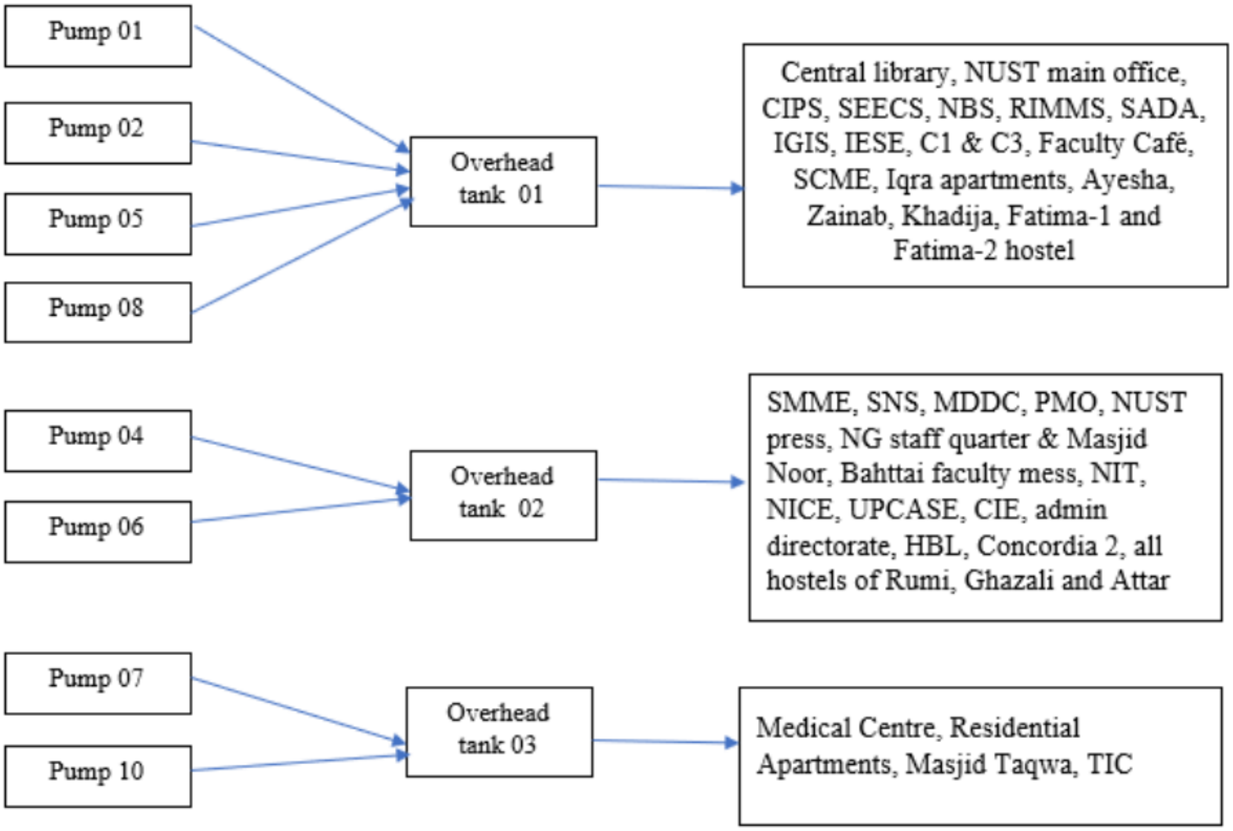

Figure 8: Water Distribution Plan

CHAPTER 5: RESULTS & DISCUSSION

In this section, we discuss the results of using the LSTM and Transformer models to forecast the water consumption of the site's occupants across four distinct seasons. The climatic details of the four seasons are in Table 3.

The training results indicate the LSTM model excels at accurately predicting short-term water consumption patterns. However, it is incapable of precisely anticipating long-term outcomes. During training, a prediction window of (90, 30) was utilized. The first value, 90, represents the total number of preceding timesteps taken into account when predicting future timesteps. In other words, the model makes predictions based on water consumption data from the previous 90 timesteps. The second value, 30, indicates the total number of timesteps for which the model intends to generate forecasts. The model performance graph is shown in Figure 9.

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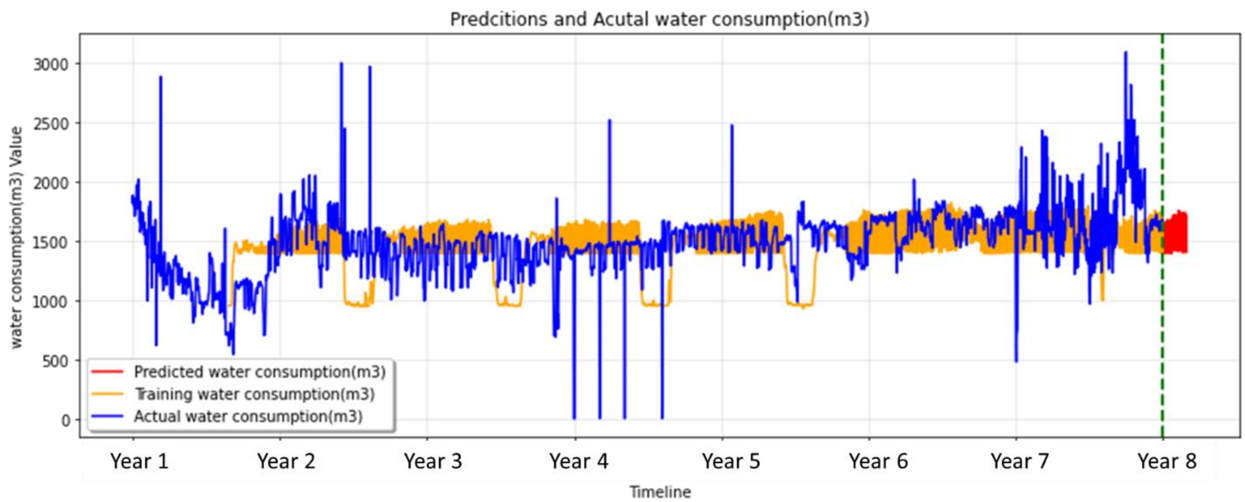

Figure 9: Prediction, training and actual water consumption using LSTM Model.

Table 3: Details of four seasons of Pakistan

Name	Duration	Climatic Condition
Cool, Dry Winter	December-February	Low temperature and minimal precipitation
Hot, Dry Spring	March-May	Relatively high temperature and minimal rainfall
Summer Rainy	June-September	Season Relatively higher temperature and high rainfall, also known as South-West monsoon
Retreating Monsoon	October-November	The monsoons gradually withdraw, leading to less rainfall

As the findings of the LSTM model demonstrate, the accuracy of the model decreases when it is used for long-term forecasting, and these models are not very effective when it comes to predicting water usage over an extended period of time. The error matrix of the trained LSTM model, which includes the root mean square error (RMSE), mean square error (MSE), and coefficient of determination (R2 score), is presented in Table 4.

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Table 4: Error Matrics of trained LSTM Model

Window Size	RMSE	MSE	R2
(10,1)	24.16	1254.98	0.976
(20,5)	38.64	9812.25	0.891
(30,12)	78.91	23565.71	0.73
(90,30)	190.45	98761.35	0.31

As shown in Table 5, the results of the trained transformer model indicate that transformers are the optimal solution for long-term forecasting of urban water consumption using climate and population data. The R2 score for forecasting one month of water consumption using the transformer model is 0.981, which is significantly better than the R2 score of LSTM, which is 0.31. In addition, the transformer model shows promising results for annual water consumption forecasting as illustrated in Figure 10 and Table 5.

Table 5: Error Matrics of trained Transformer Model for Long-term Forecasting

Forecasting Time	RMSE	MSE	R2
30 Days	18.2	892.8	0.981
120 Days	26.28	1322.48	0.968
180 Days	32.85	1457.04	0.939
365 Days	41.15	1673.82	0.917

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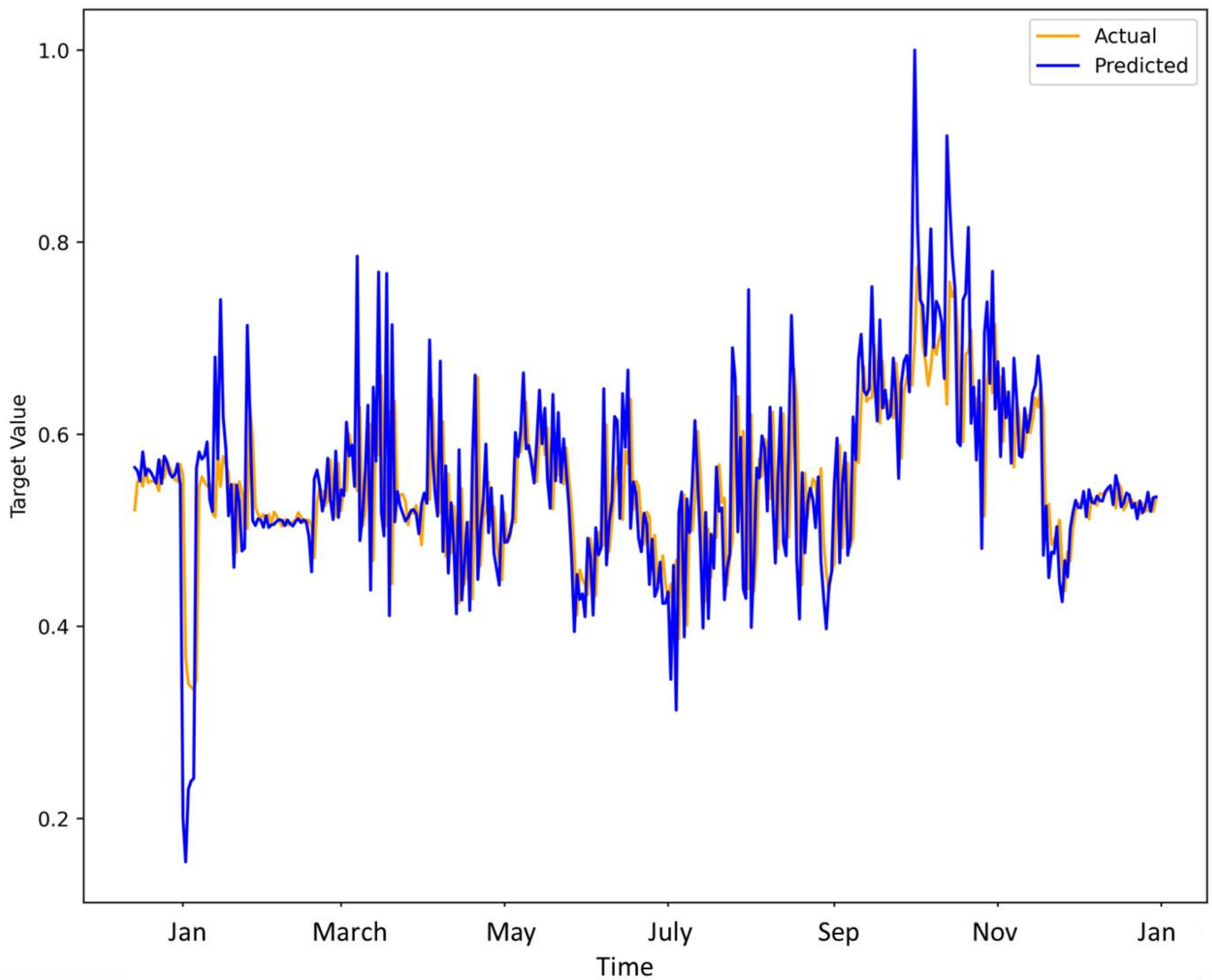

Figure 10: One-year actual vs predicted water consumption in an urban environment using transformer model

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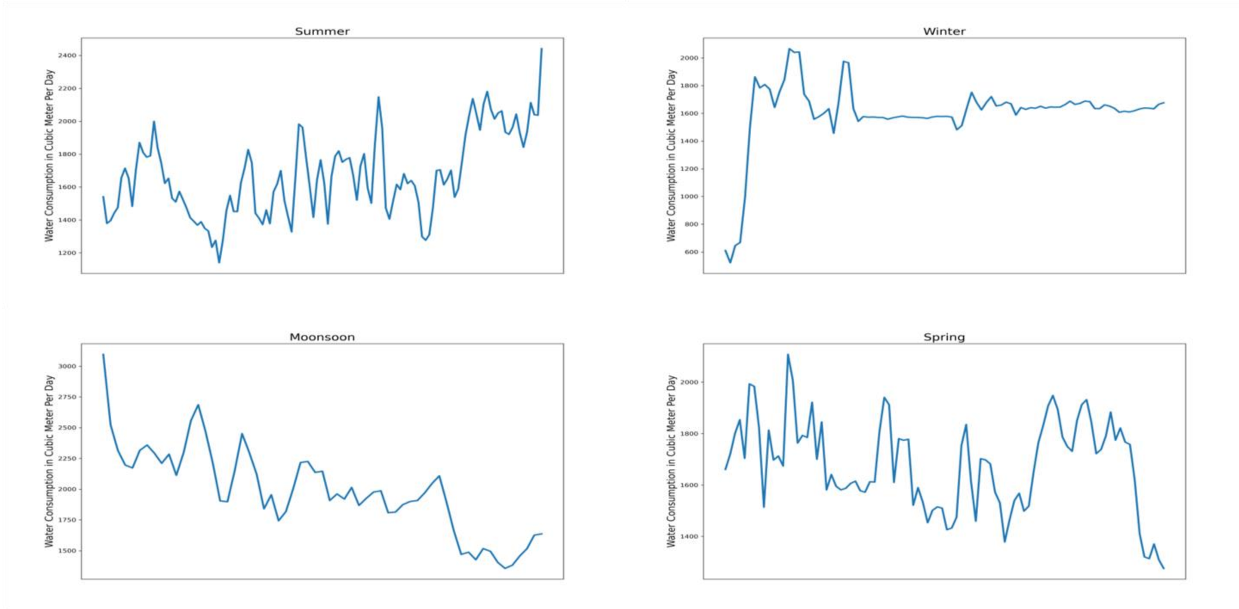

Figure 11: Seasonal forecast of water consumption for one year using proposed transformer model

Given Pakistan's distinctive four-season climate, as detailed in Table 3, we employed the proposed model illustrated in Figure 11 to calculate the country's water consumption patterns. Our observations reveal discernible trends, notably that water consumption is at its lowest during the spring and winter seasons. This reduction is notably pronounced in the winter, a period associated with reduced occupancy due to winter vacations, resulting in fewer individuals being present at the designated location.

Similarly, the graph depicting water consumption during the summer exhibits a decline, primarily attributed to the summer vacation period. During this time, individuals are inclined to travel or engage in outdoor activities, consequently reducing their presence at the monitored site.

In contrast, the monsoon season stands out as the peak period of water consumption. This is consistent with the inherent characteristics of Pakistan's monsoon season, characterized by elevated humidity levels. The combination of hot and humid conditions prompts increased sweating and discomfort, driving individuals to take more frequent showers and baths to both alleviate personal discomfort and maintain hygiene. The insights derived from the data align with our expectations based on the distinct climatic attributes of each season. The provided model effectively captures and highlights these consumption variations, enabling a deeper understanding of the interplay between climatic factors and water usage behavior within Pakistan's diverse seasons.

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CHAPTER 6: CONCLUSION

Utilizing a comprehensive dataset encompassing climate, population, and water consumption data gathered over a span of seven years, this study has forged a robust predictive framework aimed at anticipating annual water consumption patterns within urban environments. The primary objective of this framework is to foster the sustainable management of precious water resources. In pursuit of this objective, various neural network models, including Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM), and transformer architectures, were rigorously evaluated. This evaluation encompassed the refinement of hyperparameters and architectural configurations for optimal predictive accuracy.

In the realm of ANN models, their performance proved to be suboptimal, exhibiting a maximum accuracy of 70% for short-term predictions spanning just one day. The subsequent exploration of LSTM models unveiled their potential for accurate predictions in short-term scenarios. The coefficient of determination (R2 score) for forecasting water consumption over one day stood at an impressive 0.967. However, as the prediction horizon extended to 30 days, the R2 score diminished to 0.31, indicating that LSTM models might excel in capturing short-term trends.

Remarkably, the transformer models emerged as the preferred choice for long-term forecasting of water consumption. These models demonstrated the capacity to predict water usage trends up to a full year in advance, yielding an impressive R2 score of 0.917. The strength of transformers in capturing intricate temporal relationships, even over extended periods, reinforces their suitability for long-term forecasting tasks.

Significantly enhancing the scope of previous research, this study's dataset spans an extensive seven-year period, providing a more robust foundation for predictions. Additionally, the study stands out by enabling year-long forecasts, a notable advancement over prior works constrained by a maximum of three years of data for predicting one month's water consumption.

In summation, this research's contributions are substantial. By extending the prediction horizon to encompass a significant one-year period and by leveraging a comprehensive and extended dataset, the study surpasses the limitations of previous research efforts. The outcomes of this study offer invaluable insights for policymakers and water resource managers, facilitating

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informed decision-making and advancing the prudent and sustainable utilization of urban water resources.

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