Journal of Theoretical and Applied Information Technology
31st July 2021. Vol.99. No 14

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

METEOROLOGICAL DATA ANALYTIC SYSTEM: DESCRIPTIVE AND PREDICTIVE ANALYSIS

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ABSTRACT

Weather can be described as the status of the atmospheric conditions at a specific time. on the other hand, climate is the weather's status over a long period. both are very important for people's life management on multiple levels. Weather prediction is a complicated process that requires input from experts. This paper describes a weather business intelligence solution starting from requirements gathering and analysis all the way to the creation of a dashboard with weather prediction capabilities based on a machine learning technique to fulfill the business needs. In this paper, we used Long Short-Term Memory (LSTM) to predict the weather with high accuracy.

Keywords: *Weather Prediction, Weather Dashboard, Weather OLAP, Temperature Prediction, Climate Change Indicators, LSTM, Data Architecture, Weather Analysis, Power BI, SQL Data Tool.*

1. INTRODUCTION

Weather is the temporary status that describes the temperature, clouds, rains, and winds. On the other hand, the climate is the dominant weather status over a long period. Weather and climate play a critical role in helping numerous stakeholders make business decisions and plan daily activities. For example, farmers rely on this knowledge to control the agricultural process [1]. Weather prediction is usually complex since it is affected by various atmospheric phenomena. Thus, many weather stations are distributed across cities to produce reliable weather parametric values that help specialists analyze and generate reports [2]. Weather experts can easily understand and analyze weather parametric values. However, the general public needs user-friendly indications and signs to understand such parameters. Therefore, most of the weather stations construct interactive platforms that include visual guidance and charts.

Information technology should enable businesses to understand their ranking among competitors, be familiar with their customers, and maintain good relations with their partners [3]. Business intelligence (BI) helps modulate the quality of the information given to decision-makers since it offers previous (historical), current (near real-time), and predictive (future) perspective for business operations [4]. Business intelligence solutions usually handle data collection, data transformation, data storage, and data analytics. This includes data mining processes, data visualizing, reporting, and business achievement management [4]. Business intelligence solutions can deal with vast amounts of structured and unstructured data to achieve new business opportunities. Hence, many sectors such as retail, telecommunication, fashion, and human resource industries benefit from business intelligence [5-7].

A BI dashboard is a graphical interface that offers a brief insight into business trends, objectives, and progress. This paper describes a weather business intelligence solution starting from requirements gathering and analysis all the way to the creation of a dashboard with weather prediction capabilities based on a machine learning technique to fulfill the business needs.

The weather dashboard should be readable and straightforward, as it serves users with varying levels of expertise. This paper presents a creative analytic weather dashboard as a simulation for a real weather station website based on data collected from global weather agencies. While weather experts make their predictions for a specific period based on many domain factors, we aim to predict temperature beyond the given period using the well-known Long Short-Term Memory (LSTM) machine learning algorithm [8] explained in section 5.

The rest of this paper is organized as follows: Section 2 presents the related work; section 3 describes the Weather Station Business Intelligence specifications; section 4 presents the architectures of the proposed BI system; section 5 contains the predictive analysis of our system; section 6 describes the visualization of our system, and section 7 concludes the paper.

2. RELATED WORK

Weather prediction and forecasting are reliant upon the Information and Communications Technology (ICT) field. Traditional methods of presenting weather have been enhanced due to the ICT evolution era, thus increasing competition between weather forecasting agencies. In this section, we will explore some well-known weather dashboards and provide an insight on the research that has been conducted in this field.

Arabia Weather[1] is a Jordanian weather website that first reported on Jordan's main regions and later expanded to cover different Arabian areas. The website has a colorful and straightforward interface that shows hourly temperature, wind speed, and humidity for up to 14 days. Additionally, it provides the user with activity recommendations. Arabia Weather does not provide the user with the historical temperature; in addition to that, regions elevations are shown in a tabular (non-interactive) view. AccuWeather[2] is an American weather forecasting media company that shares daily videos for the USA's weather forecast. AccuWeather's written reports support most of the countries in the world. The AccuWeather website displays the weather status for up to 30 days. However, no historical information is provided, and the regional elevations and activity recommendations are missing. StormGeo[3] is a Norwegian weather service provider that also supports other services in the weather domain. StormGeo's website displays seven days weather forecast for most of the regions worldwide. Additionally, it shows the atmospheric phenomena analysis in multiple regions, excluding the Middle East. The website's visuals are straightforward. However, none of the above services provide the user with climate parametric values.

The artificial intelligence and machine learning models are widely used in the weather prediction. The model learns to predict the future weather readings based on previous ones, and recent studies state that machine learning model results are more accurate than the ordinal statistical ones [2].

Photovoltaic Power (PV) is a renewable energy resource. PV generation heavily depends on the current weather and climate. Hossain et al. aimed to predict the next 24 hours' PV power generation rate based on historical weather data, historical PV power generation rate, current weather forecast information, and the solar irradiance historical data [9].

Their historical weather data had solar irradiance, temperature, wind speed, and humidity as attributes. While the current weather forecast data had the following attributes: temperature, wind speed, humidity, and sky type. Solar Irradiance historical data was processed to generate multiple clusters; then, each cluster was associated with a corresponding sky condition category based on Oceanic and Atmospheric Association [9].

In addition to the above data sources, time and month indices were also used to predict as they were all passed to a "long short-term memory neural network" (LSTM). The achieved accuracy was: 52% for spring, 62% for summer, 77.7% for autumn, and 63.2% for winter, according to the Mean Absolute Percentage Error (MAPE). Summer season PV power generation prediction was analyzed using different periods, 6 hours with 71.4% accuracy, 12 hours with 61.5% accuracy, and 24 hours with 62%. Hossain et al. also compared their proposed work with other models such as Recurrent Neural Network (RNN) that produced 70% accuracy and Generalized Regression Neural Network (GRNN) with 66% accuracy [9].

Singh et al. aimed to create a low-cost weather forecasting system using machine learning techniques [10]. The authors introduced a sensors-based rain prediction system using real-time sensor

[1] https://www.arabiaweather.com/
[2] https://www.accuweather.com/
[3] https://www.stormgeo.com

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

data. The data used to build the model was Delhi's weather data over the past twenty years. The dataset included temperature, humidity, pressure, and rain values. All attributes were averaged and used in the model's training [10]. The temperature, humidity, and pressure sensors were attached to a microprocessor to produce real-time values to predict the current rain probability. Their prediction was based on the random forest technique. The data was divided into 75% for training and 25% for testing with a resulting accuracy of 87.90%, which is considered high [10].

With the risky nature of floods and their threatening consequences, there is a need for a system that predicts rainfall levels. To that extent, Ardiansyah et al. proposed a project that used a microprocessor connected to temperature, rain, and humidity sensors to produce alerts and rainfall levels statements. The prediction was based on fuzzy logic; sensor readings were all entered into the fuzzification unit in order to apply inference rules to produce the output. The proposed system had thirty-two rules and five output classes/values (Wet, Drizzle, Cloudy, Sunny, and Heavy Rain). The sensors' validation was achieved using a thermometer and thick film technology datasheet – TeleControlli [11].

As discussed earlier, changes in meteorological characteristics have a significant impact on our lives. Thus, accurate prediction of possible weather and climate changes is critical. Diao et al. predicted future meteorological elements using advanced methods such as artificial intelligence rather than traditional methods used in the past, such as mathematical methods [12]. To construct a "short-term weather forecast model" based on "wavelet denoising and Catboost," Diao et al. used the Beijing Meteorological Administration data. The data was recorded and analyzed every hour for more than three years, with an extremely long period and wide distribution.

Diao et al. suggested and carried out additional learning functions in advance via data mining to enhance the precision and minimize the convergence rate. Their approach can be categorized into five categories: data cleaning, selection of features, incorporation of spatiotemporal features, and denoising wavelets [12].

Before building and testing the learning model, the authors used "Wavelet Denoising, Wavelet transformation," a time-frequency analysis method. Finally, in the "short-term weather prediction model," As the learning model, "Catboost," which has the best performance among current GBDT methods, is used. The test results have shown that the proposed "short-term weather forecast model based on wavelet denoising and Catboost" can substantially reduce the learning model's convergence time and significantly improve prediction accuracy compared to conventional methods of LSTM, random forest, and Seq2Seq. For example, LSTM achieved a someday accuracy of 0.3143 on the same day, random forest achieved 0.3859, while the authors' proposed method achieved 0.5525 [12].

Furthermore, Fente et al. used an artificial neural network to predict weather conditions [24]. The data was obtained from the National Climate Data Center for the years between 2007 and 2017. The data consisted of temperature, wind speed, visibility of dew levels, precipitation, and moisture. They used the neural network Long-Short Term Memory (LSTM) technique to predict future weather conditions. The data was processed as input to a recurrent neural network (RNN). They trained neural networks with multiple combinations of data mentioned previously, the data used in the past, and the current status. The authors forecasted future weather by training the LSTM model using these variables. The LSTM achieved a high accuracy of 96.06% [13].

Al-Omari et al. constructed a computer system using Hidden Markov Models (HMMs) that can be used for the next 24 hours to estimate the "McIntosh class" and the solar flare region for the sunspot community being investigated [25]. The authors gathered data from the Space Weather Prediction Center (SWPC). Dates, locations, region, extent, McIntosh class, active region numbers (NOAA), and the class of associated sunspot events were represented in the SWPC sunspot catalog. As a training package, the authors used 80 percent of the data, and the rest was used as a test set. The average performance was 71% [14].

Anandharajan introduced a linear regression machine learning model to predict the next day's temperature and rainfall with a reported accuracy of 90% [2]. On the other hand, our model predicts the next 30 days. Our goal was to fill the gaps observed in the previously described solutions, as we will highlight in this paper. Our proposed model can predict the temperature for up to 14 days with an

Journal of Theoretical and Applied Information Technology
31st July 2021. Vol.99. No 14

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

accuracy of 89%. Additionally, we created a user-friendly visualization tool.

3. WEATHER STATION BUSINESS INTELLIGENCE

Generally, business intelligence solution implementation starts with understanding the user's needs, known as requirement engineering [15]. The requirement engineering process is to gather, define, clarify, and document the requirements. The most important requirements are the business requirements, they describe the system from a high-level perspective and do not imply a job that the system must do but rather what the business itself requires. Business Requirements describe such a system's main objective and clarify the primary targets, data sources, and business metrics. The proposed solution's business requirements can be summarized into Daily Activity Management, Cultivation Sustainability, and Weather-based Business Opportunities Recognition. The requirements with their data sources, business group involvement, and business owners are described below:

3.1. Daily Activity Management

People are usually interested in real-time temperature and wind speed to arrange their daily activities. The project will provide real-time weather indicators (temperature, wind speed, pressure, and weather description). Open Weather Map (OWM) website[4] will be the data source to fulfil this requirement. Open Weather Map (OWM) website provides a real time current weather API. The data includes the temperature, wind speed, pressure, and weather description attributes. Sampled data needs to be created in order to get the temperature of different areas with different elevations.

Business groups involvement for this requirement can be summarized as follows:

- Business analyst: to specify business needs and understand stakeholder's point of view.
- Data engineers: to collect, clean, and prepare data.
- Data analyst: to Model and convert data in order to extract needed information.
- Visualization Engineer: to explore data before working with and consequently, to properly choose the visualization techniques used in the project to meet the requirements.

The business owners for this requirement are the people interested in weather in general.

3.2. Cultivation Sustainability

Cultivation is affected by weather conditions; some plants need more water than others. For example, some plants need direct sunshine, while others cannot survive in high temperatures. Our system aims to help farmers take necessary actions (such as moving plants, changing irrigation rates, etc.) based on future weather predictions of the temperature, wind speed, or rainfall. In Amman, Jordan's capital, agriculture plays a vital role in economic stability, especially in the Dead Sea region, where the seasonal crops are grown all year round. Open Weather Map (OWM) will be used as a data source to fulfill this requirement

Additionally, for predicting the temperature beyond five days, the machine learning model can provide a prediction for up to 30 days. To view the weather situation for more than 30 days, users can use historical data to help farmers predict the temperature based on historical perspective. This data is also provided from OWM.

Business groups involvement for this requirement can be summarized as follows:

- Business analyst: to specify business needs and understand stakeholder's point of view.
- Data engineers: to collect, clean, and prepare data.
- Data analyst: to Model and convert data in order to extract needed information.
- Visualization Engineer: to explore data before working with and consequently, to properly choose the visualization techniques used in the project to meet the requirements.

The business owners for this requirement are farmers and farm owners

3.3. Weather-based Business Opportunities Recognition

Climate is a dominant weather condition observed for an extended period in a specific location. Some business opportunities depend mainly on weather and regional climate. This project should help investors make decisions based on Jordan's historical weather data and climate change indicators data. The data sources that will be used are:

- Historical data from open weather map website

[4] https://openweathermap.org/

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

- Climate change indicators data from HDX website[5]

As this requirement needs business metrics, they will be as the following:

- Arable land (% of the land area)
- Renewable energy consumption (% of the total final energy consumption)
- Urban population (% of the total population)

The involved business groups are:

- Business analyst: To specify business needs and understand stakeholder's point of view
- Data engineers: To collect, clean and prepare data
- Data analyst: To model and convert data in order to extract needed information
- Visualization engineer: To Explore data before working with and consequently, to well choose the appropriate visualization techniques used in the project to clearly meet the requirements.

The business owners are:

- The organization's CEO
- The organization's Business Analyst

4. PROPOSED ARCHITECTURE

BI framework designers cannot build an effective BI solution at once as it consists of different components. Thus, these components should be studied and their relationships analyzed. The system users, business operations, data needed, and analysis performed fall under the BI architecture framework's umbrella [16]. The framework components such as people data, and technology should join up to assure seamless functionality [17]. The BI Framework consists of four architectures: information, data, technical, and product architectures, as Figure 1 shows.

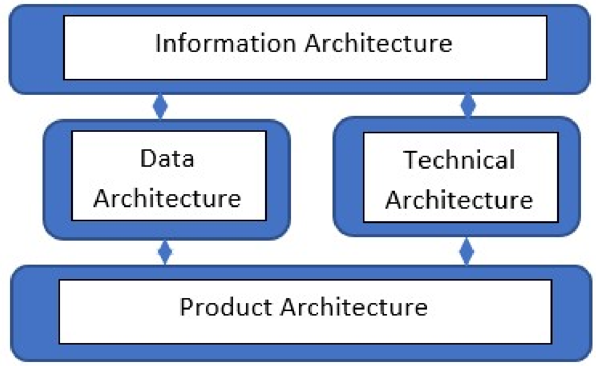

Figure 1. BI Architecture Framework [16]

4.1. Information and Data Architecture

Information architecture illustrates the process of gradually transforming data into useful information starting from the data source (such as Web, Cloud, API, Drive and Database) to the BI application (such as Dashboard, Scorecard, and Report).

The data architecture defines the data's life from its generation to consumption in detail going through data collection, data preparation, data integration and storage processes. Information providers supply data source details while consumers provide metrics and transformations. Both the information and data architectures are correlated; hence, they are described together in Figure 2.

[5] https://data.humdata.org/dataset/world-bank-climate-change-indicators-for-jordan

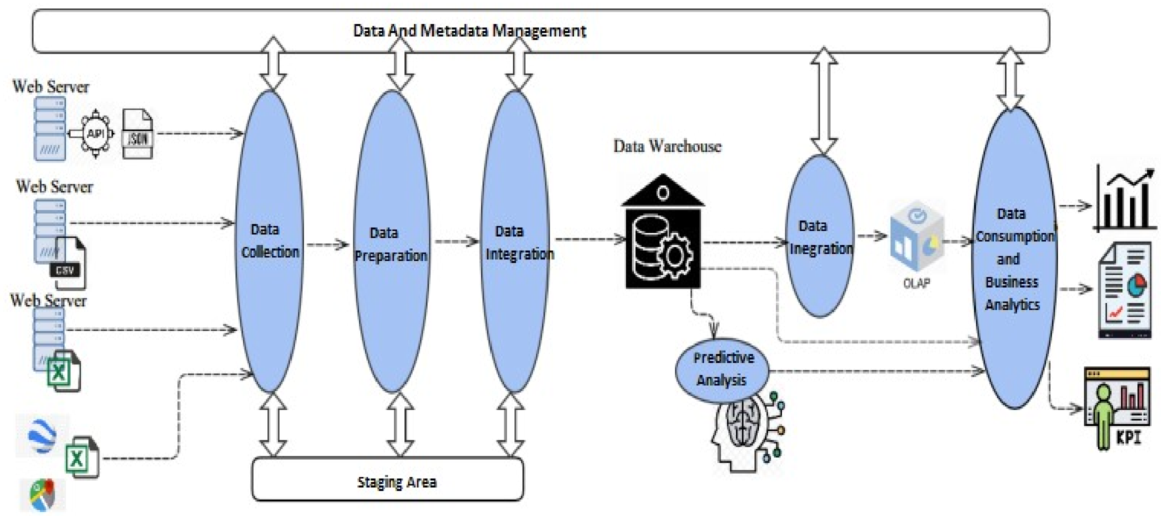

Figure 2. Data and Information Architecture

4.1.1. Data Collection:

Data collection is the process of gathering the data from different sources and formats. Various data was collected from different sources as summarized below:

Historical Weather Data is downloaded from OWM in CSV format

Current (Real Time) weather data is collected from OWM through a web API in JSON format

Five days weather data forecast is collected from OWM through a web API in JSON format

Jordan climate change indicators data is downloaded from HDX in XLS format

Amman's regions coordinates and elevation data is collected manually from Google maps and Google Earth.

4.1.2. Pre-processing, feature selection, and extraction

It is the process of extraction and selection operations applied on the collected data. They are done as follows:

The original historical weather data has 16 features (Table1), while the resulting ones after pre-processing and features selection process are 8 features (Table 2). The feature selection process is applied to drop the unimportant features from the dataset for both the descriptive and predictive analysis.

4.1.3. Data Sampling

Historical weather data has around 361,686 records; each record contains the weather conditions for a specific hour between January 1979 and March 2020. Instead of having 24 records for each day, only the average representative will be used.

OWM data covers only 17 regions in Jordan, thus the rest of the region's temperature are estimated based on the relation between the elevation and temperature. i.e., reference region is chosen to estimate the rest of the region's temperature based on the elevation's differences.

The five days weather forecast data contains a record for each 3-hours of the day. Instead of that, one average representative record is used for each.

4.1.4. Data Transformation and Integration

Current (real time) weather data for the 17 regions are integrated into one table. The historical data and 5 days forecast data are transformed to the same type in order to integrate them together.

4.1.5. Data Storage:

The data from multiple sources is stored in a Data Warehouse, where OLAP cube is created to represent a specific dimensionality of the data.

Table1. Historical weather table original attributes

1. City_Name (Mainly Amman)	2. Lat (Latitude)	3. Lon (Longitude)	4. Main.temp (Temperature Average)
5.Main.Temp_min (Minimum Temperature)	6. Main.Temp_max (Maximum Temperature)	7. Main,feels_like (Feels Like Temperature))	8. Main.pressure (Air Pressure)
9. Timezone (Region's time zone)	10. Main.humidity (Air Humidity)	11. Wind.speed (Wind Speed)	12. Wind.deg (Wind Degree)
13. Clouds (Clouds quantity)	14. Weather.description	15. dt (Date time) hour by hour	16. dt_iso (Dupliated Date time)

Table 2. Resultant historical weather table attributes

1. Avg_Wind_speed (Average hourly wind speed per day)	2. Avg_Wind.dir (Average hourly wind degree per day)	3. date (Date)	4. Absolute_min (Minimum of hourly minimum temperature per day)
5. Absolute_max (Maximum of hourly maximum temperature per day)	6. AVG_Humidity (Average humidity per day)	7. AVG_Pressure (Average of hourly Pressure per day)	8. AVG_wind_speed (Average hourly wind speed per day)

4.1.6. Processing

The historical data is used to train a machine learning model to predict the next 30 days temperature.

4.1.7. Visualization and Analytics:

Charts and creative visuals represent the data in terms of current weather status, weather forecast, and weather prediction to produce an interactive dashboard. For example, Jordan's map represents the relation between the region's elevation and the temperature. A linear plot is used to describe the machine learning model predicted weather. Additionally, a heat map represents the OLAP's result. The historical temperature is represented in a calendar view, and simple symbols (sun or clouds) are used to describe the weather data given by the OWM website. Figure 10 summarizes the visual representation.

4.2. Technical and Product Architecture

The technical architecture specifies the techniques and methods used to implement the information and data architecture[18]. The product architecture specifies the products needed to meet the project's requirements. Their properties and how they are integrated are also defined in this architecture [19].

Since every product may utilize several technologies, we usually start by detecting the data and information requirements and architecture, then the techniques needed for them and the products to use subsequently [18]. The project's technical and product architectures are shown in Figure 3 and described in the subsequent stages:

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31st July 2021. Vol.99. No 14

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

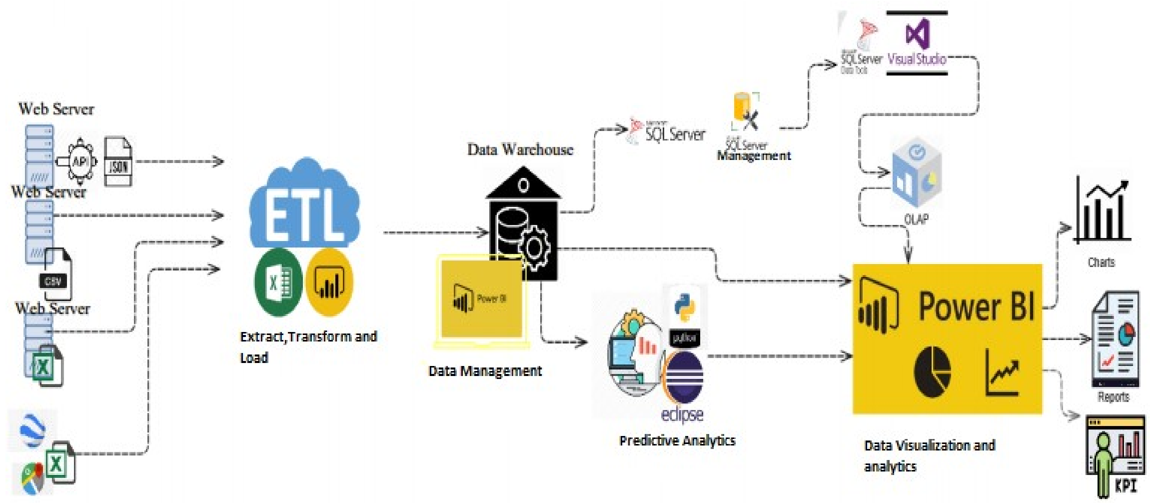

Figure 3: Technical and Product Architecture

Stage 1:

Microsoft Power BI is used to extract JSON data representing the current and the next five days weather at Amman's central station and the current weather for another 17 regions via OWM API. The data is also pre-processed in Power BI.

The historical weather data is exported from OWM via direct download, it is pre-processed and sampled using Microsoft Excel.

The climate change indicators data is downloaded from HDX website, then loaded into Power BI.

Since OWM data only supports 17 regions, the rest of Amman's main regions data is collected manually. Afterwards, the data is inserted into Microsoft Excel file and loaded into Power BI. The sampling is done in Power BI.

Stage 2:

The data warehouse is created using Power BI to store the data. The integration process is done using power BI in multiple different ways. The current temperature for all supported regions is integrated into one table directly when being read from their sources. Historical data and five days weather forecast data are integrated in a different way since one of them is considered a real-time source (the data is not permanent) and the other one is not. A power query function is used to append the newly refreshed data to a separate file then it is inserted again into power BI and combined with historical data table.

Stage 3:

Python programming language, Keras library and Eclipse IDE are used to implement the machine learning algorithm, which construct the machine learning model using the historical data. After that, Python code is implemented into power BI to make continuous temperature prediction based on the table resulting from the integration between the historical and five days weather data.

The registered regions weather data is integrated into Microsoft SQL server. The date and temperature description tables will be extracted from current weather main table and will be also integrated into Microsoft SQL server in addition to Coordination-Elevation table to create a sample data OLAP cube using Microsoft Visual Studio and Microsoft SQL server data tool.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Stage 4:

All the mentioned tables are used to produce interactive user views including visuals, charts and KPI using Power BI.

5. WEATHER STATION BUSINESS INTELLIGENCE PREDICTIVE ANALYSIS

Predictive Analysis refers to exploiting the data in statistical and machine learning methodologies to recognize future results' probabilities based on the previous readings/data. The aim is to go further than report what has happened in the past and estimate and analyze what will happen next [20].

Many organizations consider this technology due to the massive amount of data generated each hour, the availability of professional computers, easy and user-friendly software existence, and the competitive economic market. As a result, Predictive Analysis has been heavily used in statistics and business analysis [20]. Since this project aims to predict the future temperature based on the previous ones, we rely on a model that efficiently realizes the modality of the data sequence. Thus, we use the LSTM model to predict the temperature for the next 30 days in Amman, as described in the next section.

5.1 LSTM

Time series forecasting is the process of predicting an output while referring to sequence-dependent inputs such as daily temperature. Recurrent Neural Network (RNN) has been used to solve such problems. The LSTM is a variation of RNN that is widely and efficiently used to predict time-series output [21]. As shown in Figure 4, the RNN applies the same function for each input, and produces sequence-dependent output, i.e., it depends on the current input and the output produced from the previous input [22].

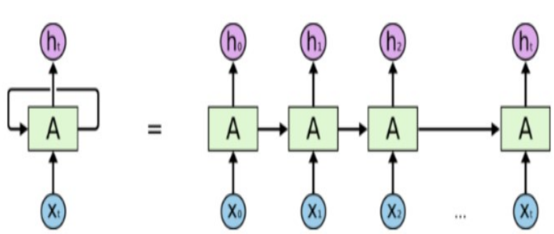

Figure 4: RNN Cell [24]

The LSTM has been developed to solve RNN large gaps limitations [8]. The LSTM block has many components such as the input, the output, and the forget gates [8]. The Figure 5 below shows the LSTM cell's main components.

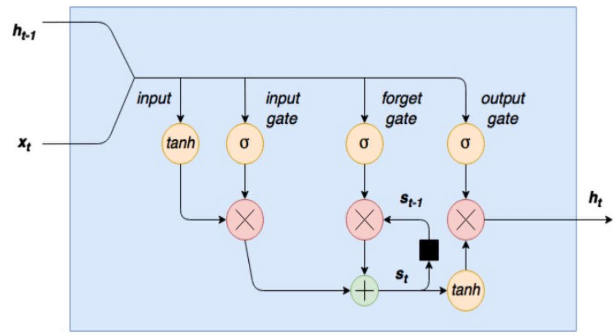

Figure 5. LSTM Default Cell [27]

As shown in the Figure 5, x_t (the current input) is combined with h_{t-1} (the previous output); let call this combination XH. Step 1: XH is passed to a tanh layer (activation layer). Step 2: XH is also passed to the input gate that uses a sigmoid function. The goal is to discard any unnecessary components from the input since the sigmoid generates values between 0 and 1 (0 is to "kill-off" certain input while 1 is to pass it). Step 3: the results from steps 1 and 2 are multiplied. Step 4: the previous state variable S_{t-1} is added to step 3 results; this step is controlled by the forget gate that decides which previous state value to remember and which to forget. Step 5: a tanh layer is used to generate the output, which is also controlled by another sigmoid layer [23]. Each LSTM cell has a number of hidden layers. Each tanh, sigmoid, or hidden state consists practically of multiple layers. Generally, the activation function could be Sigmoid, tanh ("Hyperbolic tangent"), or ReLU. Table 3 shows the output range for each of them.

Table 3. Activation Functions

Activation Function	Output Range
Sigmoid	0 - 1
Tanh	-1 - 1
ReLU	0 – infinity i.e., Linear if input >0 (it is more sensitive to input)

In this project, we used LSTM to predict the next 30 days' temperature based on the previous 30 days. One LSTM layer is used with 300 hidden layers, ReLU activation function, 30 batch size, and 100 epochs. The resultant accuracy was 89.4%. The predicted temperatures are displayed in the weather dashboard. Table 4 represent our experimental results as we have tried to tune the model by changing epochs and the number of hidden layers.

Table 4. Experiments Results with Fixed Epochs and Fixed number of Hidden Layers

Epoch	The Hidden Layers	Accuracy
100	100	83.5
100	200	88
100	300	**89.4**
50	300	64.2
90	300	**89**
200	300	87.5
300	300	57.5

6. BUSINESS INTELLIGENCE VISUALIZATION

This section includes snapshots of the weather station's main views. Figure 6 shows Amman's central station's current weather status, activities recommendations based on the current weather, and five days weather forecast. Users can check the hourly weather (every three hours) on any day of the next five days.

Figure 7 represents climate change indicator's value across different years. Users can change the period of the plot (in years). The indicator name can be selected from a side slider.

Figure 8 shows Jordan's map with the region's elevation (especially for Amman's main regions). Once the user clicks on any area, its estimated temperature will appear. As mentioned earlier, this temperature is calculated based on the elevation.

Figure 9 is the main view; it displays the temperature predictions and estimations for an extended period. The first plot shows the predicted temperature for the next 30 days per LSTM results. A calendar is shown below this plot to help users check the estimated temperature for any day of the year based on calculations using historical weather data.

Figure 10 shows the sample OLAP representation in Power BI; it represents the maximum temperature in Jordan's regions across multiple days.

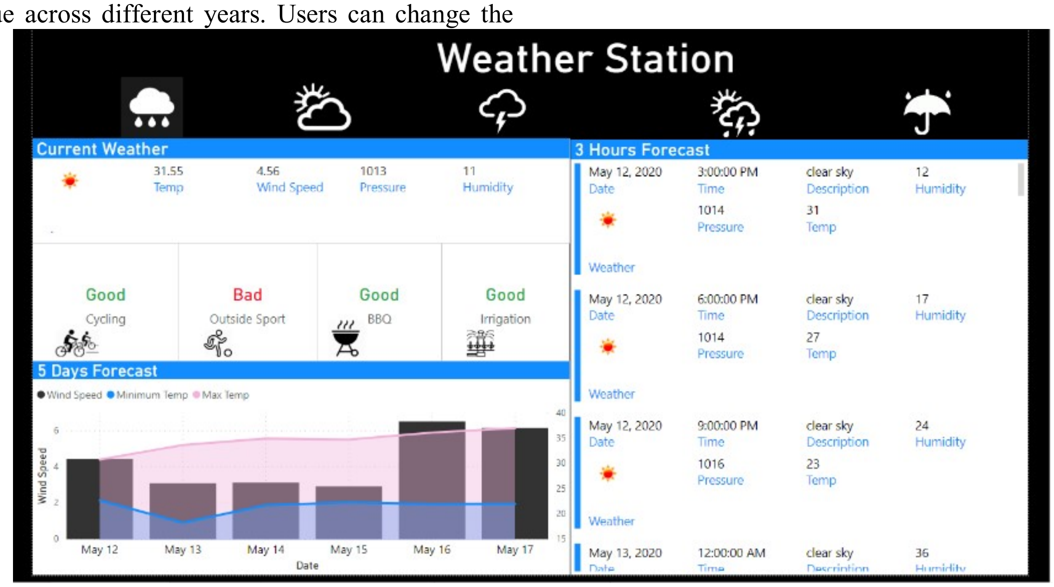

Figure 6. The Weather Dashboard View

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

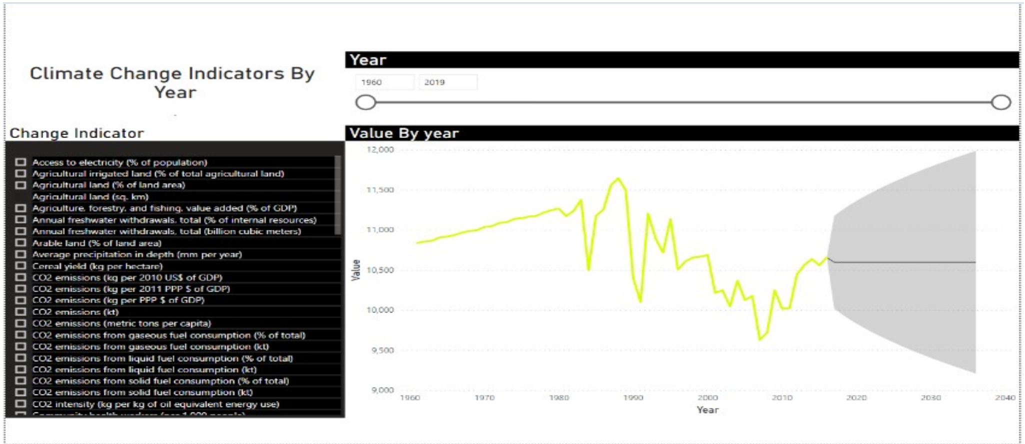

Figure 7. Climate Change Indicators View

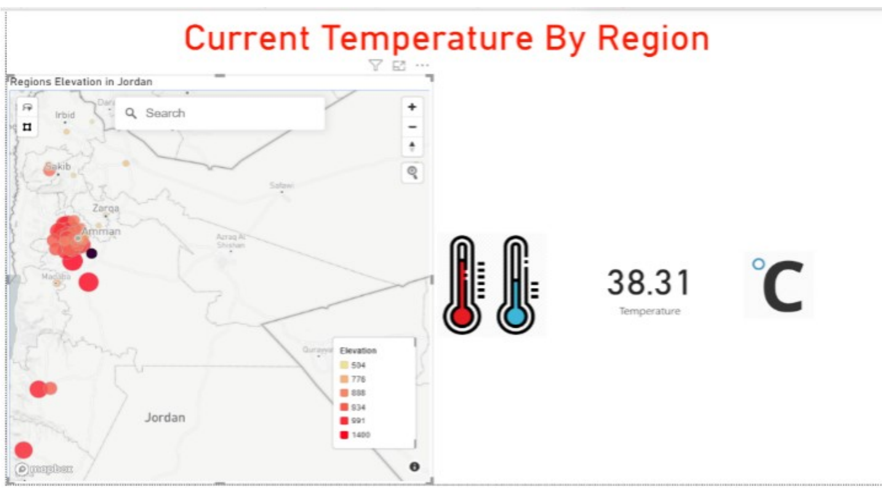

Figure 8. Temperature by Region View

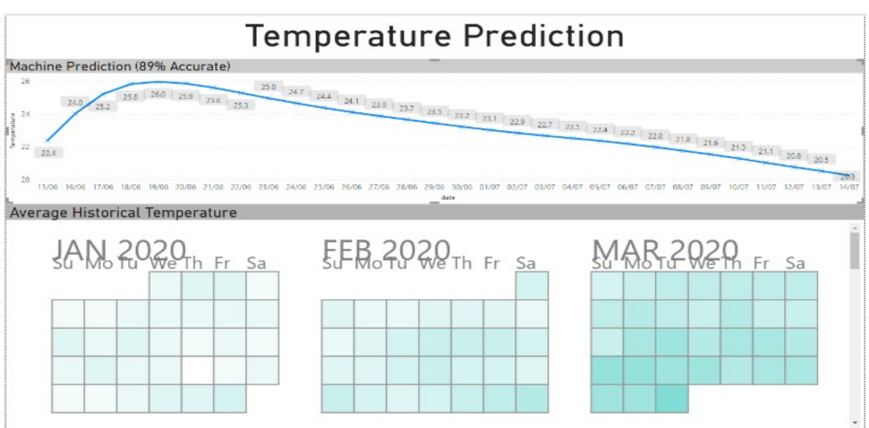

Figure 9. Temperature Prediction View

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

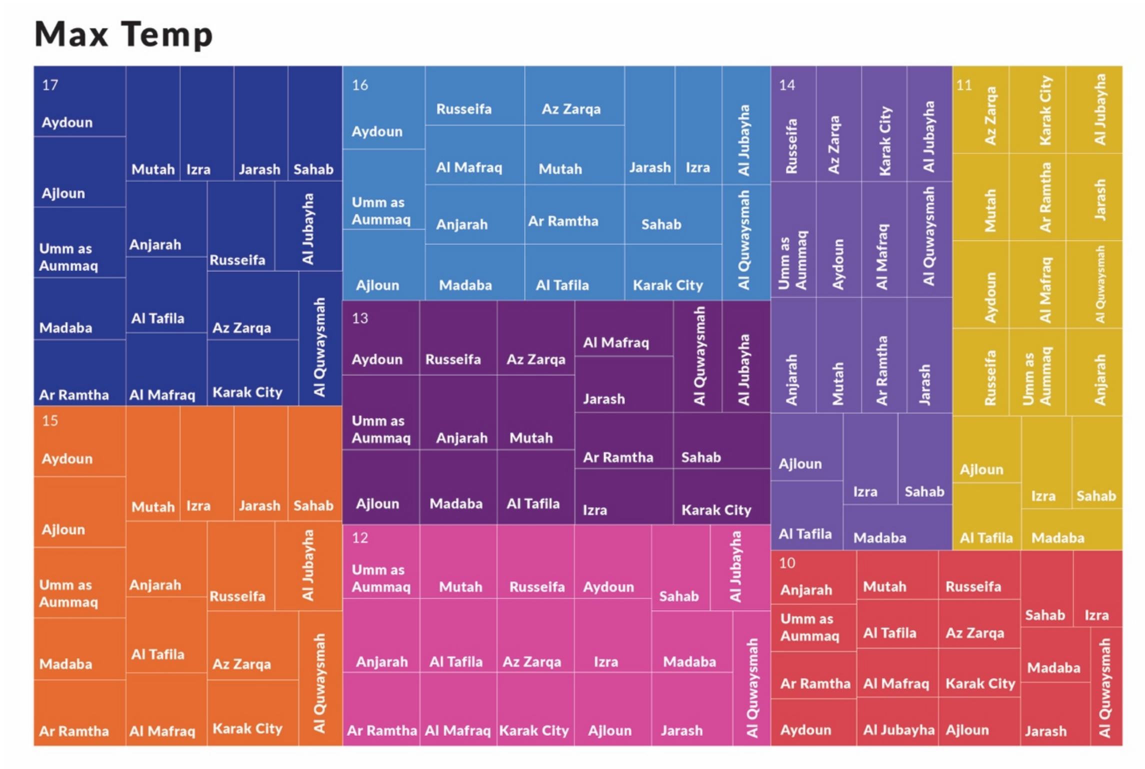

Figure 10. OLAP Sample View

7. CONCLUSION AND FUTURE WORK

Most people are interested in knowing the weather status as most activities are affected by weather conditions. Furthermore, many business opportunities rely on the region's main climate. Motivated by those facts, we aimed to create a usable and accurate weather station tool.

We collected the desired weather and climate data, made the needed transformations and integrations, and processed a subset via a machine learning technique (LSTM) that can predict the temperature for up to 14 days with an accuracy of 89%. Finally, we created a user-friendly representative view.

Global warming and the Ozone hole are the leading causes of the rise in the earth's average temperature. The climates changes vary from time to another, i.e., some summers are hotter than others in different years. At the same time, some years have an excellent overage of rains; others do not. Thus, we cannot rely on the model's previous learning as old data may have different patterns than the new one. In our future work, we will use incremental learning to train the model using the newly observed data. Incremental learning is how the model keeps learning whenever new data instances appear over time [24, 25].

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