A Comparative Study of Statistical and Deep Learning Model-Base weather Prediction in Albania

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Abstract: - Rainfalls are one of the most important climate variables that today impact significantly different sectors like agriculture, energy, industry, and so on. Agriculture is one of the most sensitive sectors to climate change because rainfalls in this case, directly affect the positive progress of corps activity. In this case, forecasting rainfalls would help farmers to effectively survive the increasing occurrence of extreme weather events, plan their farming activities, and reduce costs. On the other hand, circular economy (CE) promises a strategy to support sustainable and regenerative agriculture by supporting the sustainable management of water based on water resources. This paper aims to determine the best method for forecasting a natural phenomenon such as the rainfall, that today in Albania, as a result of the unpredictable flows that it often has, is a major problem in the field of agriculture. In this study, the rainfall model based on statistical methods, Auto-Regressive Integrated Moving Average (ARIMA), Error, Trend & Seasonal (ETS) and deep learning models, Long Short-Term Memory Network (LSTM), and Deep Forward Neural Network (DFNN) was developed. The study area that will be used for rainfall forecasting is Albania with a time interval between January 1901 and December 2022. The period that will be used for prediction will be January 2023- December 2024. The performance of each of the models used has been evaluated by using Root Mean Square Error (RMSE) where we also used the comparison of training and validation loss curves to analyze and avoid the model overfitting in the training phase. The results showed that from the comparison between ARIMA and ETS, ETS has the minimum prediction error value while between LSTM and DFNN, DFNN has the best performance in the evaluation metrics (RMSE) and with the best training and validation loss curves. From the final comparison, ETS was better than the DFNN model with the lowest root mean square error (RMSE). ETS was the best model and provided higher accuracy in precipitation forecast.

Key-Words: - Rainfalls, Agriculture, ARIMA, ETS, LSTM, DFNN, RMSE.

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1 Introduction

Climate change is an issue that is ranked as a leading global matter, [1]. It is a very fundamental factor that affects different sectors of the economy of a country but in our study, we are going to focus on the sector of agriculture. Agriculture is one of the most important sectors of the Albanian economy, and being so, it is crucial to determine the factors that directly affect its sustainability. Agriculture requires the highest amount of water usage than any other economic sector globally and by adopting Circular Economies (CE), agriculture can shift from a linear approach that turns natural resources into products and waste, to sustainable practices that minimize resource consumption and waste accumulation, [2]. Also, [1], concluded that the climate crisis has to shift to a circular production and consumption model because CE (Circular Economy) is gaining worldwide attention as a sustainable alternative for the future. The practice of predicting weather conditions serves as a way for agriculture to adapt to the effects of climate change and also optimizes agricultural production by promoting sustainable development while reducing loss and improving economic results, [3]. To mitigate the negative impacts of climate change on agriculture, it is critical to consider both current and future climate changes while planning strategies for agricultural production, [3]. In this way, farmers can make profitable and good choices and also by utilizing science and technology, the practice of weather forecasting will foresee forthcoming atmospheric conditions at a specific location depending on their needs, [4].

Out of all-weather events, rainfall is one of the crucial meteorological variables that plays an important role in the existence of human beings. Hereupon, rainfall is an important phenomenon that affects daily life in various ways, including water consumption, agriculture, pollution, etc. and its prediction is of great interest, [5]. Besides being vital to the economy it can seriously damage infrastructure and crops through floods, [6]. So, based on the importance of this topic, we will forecast rainfalls using machine learning algorithms because are appropriate options for utilization in the modeling and prognostication of meteorological events, [5]. This study aims to build a univariate rainfall time series data model in Albania for the period January 1901- December 2022, based firstly on a statistical approach, ARIMA and ETS, and then on deep learning algorithms like LSTM and DFNN for various numbers of lags and horizon.

The article is organized as follows. Section 2 proposes a literature review on the definition of weather forecasting (rainfalls) impact on agriculture and management of water and also agriculture in the transition that is happening nowadays towards circular economy, and the related work on statistical and deep learning models we are going to use to forecast the rainfall time series. Section 3 presents the study area and the data sets also its main characteristics, introduces the methods and algorithms to be used, and also focuses on data and experimental design. In Section 4 the results are discussed. Finally, Section 5 presents the conclusions and some lines of future work. The motivation for this article came from the fact that in Albania, rainfall is a genuine problem that brings irreparable damage and consequences to crops and not only. And taking into consideration the aforementioned machine learning methods, we would bring a contribution to the Albanian literature in this field, since there are few or almost no studies dealing with this natural phenomenon using this type of approach.

2 Literature Review & Related Work

Nowadays, climate change is one of the most current worldwide issues, especially with irregular and unpredictable rainfall patterns, extended periods without rain, floods, and other associated phenomena. It has emerged as the primary catalyst for issues experienced across various sectors. Among the most affected ones, agriculture exhibits a significant dependence on climatic factors and is predicted to be the foremost influenced sector by climate change, [7]. Agricultural drainage, rain and storm runoff, etc. are a consequence of climate change, which is making it difficult to access water for irrigation, negatively affecting agriculture, [8]. Furthermore, the need to forecast atmospheric conditions precisely, to avoid or reduce the impact of a disaster, [9], has become a necessity. Efficient weather forecasting has the potential to enhance the agricultural sector's resilience against natural disasters, minimize damages, steer production, and enable strategic arrangements for consistent and increased productivity, [3].

Because agricultural operations are mostly controlled by rainfall allocations, [7], we are going to focus on forecasting rainfalls as their significance extends far beyond their role in agriculture as they play a crucial role in preserving the ecological balance, and have widespread positive implications for the entire ecosystem, whether directly or indirectly, [10]. Recent theoretical developments have revealed that it has a direct impact on the sustainable development of various economic sectors, including agriculture, and also plays a significant role in the circular economy, [11]. On the other hand, a circular economy has the potential to mitigate water scarcity issues by directing attention to water resources used in agriculture and implementing strategies to reduce consumption and increase water reuse, [2]. Its implementation can ensure the conservation of resources, stimulate agricultural productivity and boost the economy, [12]. To adopt this approach, the appropriate infrastructure is needed for the rainwater to be collected in the appropriate structures for further use in agriculture. In, [2], stated that a comprehensive strategy for managing water resources should be both interconnected and circular, taking into account other systems and factors, [2]. He also stated that it is highly crucial to educate and inform the agricultural industry and its employees about CE's principles and benefits and its execution needs to be carried out at the local and why not global level, [2]. Over the past few years, there has been a surge in the utilization of machine learning algorithms for simulating atmospheric phenomena due to their ability to handle large amounts of data, provide a clear representation of the modeled phenomenon, and detect patterns or correlations in the data that aren't readily visible, [5]. In, [7], also stated that the use of Machine Learning can efficiently handle the difficulties associated with analyzing extensive amounts of non-linear meteorological data and can yield considerable benefits in the field of weather prediction, including better accuracy, faster results, and various other perks.

Some works have used different machine learning techniques mostly deep learning algorithms, to forecast rainfalls. More specifically, for our main focus, these are the following studies. In, [13], a set of methods of different data mining fields are described and compared to conclude which methods are the best to predict weather extreme conditions. In, [14], the air quality model based on the LSTM and ARIMA was developed for Malaysia on monthly data from the period of 2017–2019 using air quality data. In, [5], a set of machine learning methods was used to make predictions about the phenomenon of rain in the main cities of Australia in the last 10 years. In, [15], ARIMA and Artificial Neural Networks (ANN) were used to forecast monthly rainfall data from year 1901 to 2015 for different regions across the country of India. In, [7], shows the importance of rainfalls in agricultural production in Africa and has developed Machine Learning-based models adapted to the context of daily weather forecasting in Senegal. In, [16], a method utilizing an LSTM-based prediction model with a seq2seq structure was introduced to estimate hourly rainfall runoff. The model was tested on two watersheds located in Iowa, to predict 24-hour periods of hourly runoff. In, [17], the LSTM technique was applied utilizing the meteorological components of Eastern China's historical information, specifically for the next twelve hours following a specified time, to improve the accuracy of rainfall predictions. In, [18], simple models for estimating rainfall were developed using traditional Machine Learning algorithms and Deep Learning structures, in conjunction with climate data from five major cities in the United Kingdom covering the period of 2000 to 2020. In, [9], a discharge prediction model for flash flood forecasting in hilly areas has been developed by using LSTM networks. From 1984 to 2012, the recorded rainfall and discharge data have been transformed into hourly time series data. In, [19], two hybrid models utilizing LSTM networks to accurately predict monthly streamflow and rainfall patterns were developed. This study utilized monthly data on streamflow volume obtained from Cuntan, Hankou, Jinan, and Wenjiang (Chengdu). In, [6], a rainfall prediction model with 6 parameters was developed by using artificial intelligence and LSTM techniques, for Dhaka city from 2000 to 2014. This study focuses on developing a system for removing flood damage effects and improving agriculture using the latest approach of deep learning in time series forecast analysis. Lastly, in, [10], the precipitation records from 2021 and 2022 in Tamil Nadu's Vellore area were predicted using various machine learning techniques like ARIMA and ETS, followed by LSTM on the time-series data. In this research, two forms of machine learning and deep learning algorithms are applied to analyze a rainfall dataset to determine which approach is the most efficient in forecasting precipitation. When making this decision, one of the factors that is taken into account is their scores in terms of performance and accuracy.

3 Tools and Methodology

3.1 Study Area and Data Analysis

3.1.1 Study Area

Albania is characterized by a subtropical Mediterranean climate. The geographical features of the country are mainly defined by its mountainous terrain, rolling hills, and coastline, which contribute to the formation of an elaborate system of rivers and lakes due to its distinct geological and climatological attributes. The topography of the country predominantly comprises mountainous terrain, which is marked by the presence of copious water resources, a varied range of flora and fauna, and an extensive shoreline that stretches along the Adriatic and Ionian Seas. The northern, western, and southwestern regions of Albania are characterized by considerably higher precipitation levels compared to other areas within the country. The yearly mean precipitation measures 1,430 mm, however, notable distinctions exist in both the seasonal and spatial distribution patterns, whereby the majority of rainfall prevails during the winter season, [20]. The Albanian Alps exhibit the highest levels of humidity among various regions. In November, the precipitation levels reach a climax, whereas the period from July to August marks a nadir in this regard, with notably lower amounts, [21]. This pattern of seasonal variation indicates a distinct annual cycle in terms of precipitation. Agriculture is one of the main sources of food and economic development. Agriculture employs over 50 percent of the population and accounts for about 19% percent of the gross domestic product, [21]. Primarily, the agricultural sector heavily relies on rainfed cultivation, which is contingent upon the cyclical precipitation patterns of specific seasons.

3.1.2 Data Analysis

In this paper, we analyze the historical data on the monthly rainfall(mm) for the period from January 1901 to December 2022 (Figure 1). They were collected from the Climate Change Knowledge Portal, World Bank, [20]. Firstly, we model rainfall time series using ARIMA and ETS methods. The rainfall time series was modeled and forecasted using the Box Jenkins Model for the ARIMA method, [22], and the Exponential Smoothing State-Space model for ETS, [23]. The precipitation variable has 1464 monthly observations data and the experiments were carried out using Time-series Library (R) software.

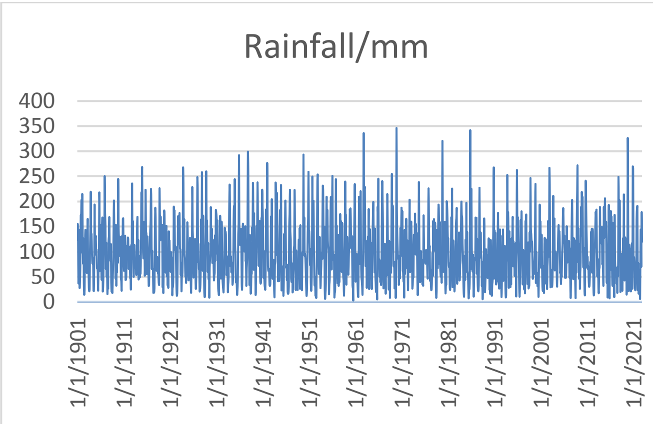

Fig. 1: Observed average monthly precipitation of Albania 1901-2021

To forecast rainfall using deep learning models, we need to calculate the data points and divide them into three sets. The dataset consists of a total of 1464 data points. It is divided into three sets: the training set (from January 1901 to December 2016), the validation set (from January 2017 to December 2019), and the test set (from January 2020 to December 2022). The deep learning models we will use to forecast are LSTM and DFNN and below we will explain the steps we should follow to put them into practice:

- *Selection of input and output data*

As we previously mentioned, the months of October - March are identified as the rainfall season in Albania. Thus, the present study explores the data of these 6 and 12 months from 1901 to 2022. There will be 732 entries for the 6^{th} step and 1464 entries for the 12^{th} step in the output and the input files. The Input parameters are the average rainfall for the 6 and 12 months of 122 years from 1901-2022. The output parameter is the average rainfall in the months of every year from 2020 -2022. The data that we will use for these models are obtained from the World Bank website.

- *Split data: training & testing Initialize model parameters*

The experiments on deep learning models are implemented in Python. The models are trained with a set of the input data, the training data set. The model types we are going to use as we have previously mentioned are LSTM and DFNN composed of six layers: one input, one output, and four hidden layers. In the training phase, the algorithm uses only 90 percent of the input data which means that from 1464 examples, only 1392 are used for training and we will keep 36 samples for validation and 36 samples for testing. These 1392 examples are chosen randomly from the overall data set. The split of the series is based on the sequential nature of the data. The first 90 % of data are used for training and the remaining data are equally divided and used respectively as validation and testing data sets.

- *Train and Test Model*

The training set is used to train the model so that it learns and reduces the error value. During the training phase, we use the validation set to control the learning process and avoid overfitting. Finally, after the model is trained, the third set of data is given to the model and we estimate the out-of-sample prediction performance. With the results obtained in this phase, we select the best deep-learning model. The LSTM and DFNN set aside 10% of the input data for testing and validation and out of 1464 samples, 36 are used for testing and another 36 are used for validation.

- *Model evaluation and comparison*

In this step, we have trained and tested the model and can generate a graph that will help compare actual and predicted output.
Also, you can have a clear vision of how accurate the model is.

3.2 Methodology

As we previously mentioned, we have selected models where two of them are classified as statistical models such as ARIMA and ETS and the other two are deep learning algorithms to forecast univariate models, such as LSTM and DFNN for forecast analysis. Our main interest is to study the predictive performance of different deep learning models for various numbers of lags and horizons, and then to compare them with the statistical approaches. The delayed data used as node values for the input layer on each model are 12, 18, and 24 and the predictive horizon is 6 and 12 months ahead. The predictive DL models and the statistical methods were evaluated based on their performance on the test dataset using RMSE. By using RMSE criteria simultaneously for forecasting estimation, we can find the fluctuations in errors. Below we give a brief introduction to ARIMA, ETS, LSTM, and DFNN.

3.2.1 Autoregressive Integrated Moving Average (ARIMA)

The utilization of the Box-Jenkins approach facilitated the construction of an ARIMA model. The ARIMA model is denoted as ARIMA (p, d, q), wherein p, d, and q correspond to the number of autoregressive parameters, degree of differencing, and the order of moving average, respectively [24]. To be specific, p signifies the autoregressive order, d denotes the degree of differencing, and q implies the order of moving average, [22].

$$\Delta^d Y_t = c + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (1)$$

Where, $\Delta Y_t = Y_t - Y_{t-1}$

If the data exhibits seasonal patterns, the corresponding models are going to be referred to as Seasonal Autoregressive Integrated Moving Average (SARIMA)models (p,d,q)(P, D, Q), [22].

3.2.2 Error, Trend, Seasonal (ETS)

The ETS model is utilized to disintegrate a given series into four distinct components, namely the level component, the trend component (T), the seasonal component (S), and an error term (E), [23]. The forecast derived by ETS is generated by computing a weighted average across all the observations contained within the time series data set. The weight values exhibit an exponential decrease as time progresses, as opposed to the fixed weight values utilized in basic moving average approaches, [23]. The weights depend on a constant parameter, commonly referred to as the smoothing parameter. Exponential smoothing models use a weighted average of past observations to give more weight to the most recent observation, with the weights decreasing over observation time, [25].

3.2.3 Long short-term Memory (LSTM)

LSTM is the top deep learning architecture for future tasks that works with long-range time-series data by incorporating memory structures to manage lengthy information and offers solutions for nonlinear time series, [26]. LSTM was created to overcome traditional neural networks' inability to link past data with the present in lengthy relationship tasks, [16]. The LSTM process deviates from the conventional neural network structure by incorporating an exclusive type of neuronal arrangement called the "memory cell". By utilizing a concealed layer framework, the LSTM network can retain data for an indefinite period, resulting in a more accurate time-based model, [17]. The memory module comprises a loop connector and three door-like structures, namely the input gate, output gate, and forget gate. The fundamental concept involves managing the gate switches by utilizing a non-linear function to safeguard and regulate the memory unit's state, and additionally manage the flow of information, whether it is being amplified or reduced, [17]. LSTM is one of the most successful techniques that address the vanishing gradients effect where they minimize it by implementing three gates along with the hidden state, [18]. LSTM neural network algorithm exhibits better pred ictive performance rather than neural networks when utilized to estimate the water depth in agricultural regions, [9].

3.2.4 Deep Feed Forward Network (DFNN)

DFNN is a type of multi-layer perceptron (MLP), consisting of a sequence of layers, where information is directed from the input layer to the output layer. The architecture of a DFNN model consists of input, hidden, and output layers where in the input layer the input vector of a sample is stored for each iteration while the output layer is the final stage of the DFNN model where the number of nodes in this layer is set according to the dimension of the output data, [27]. The learning process for DFNN is supervised learning in which the weights, during the training phase, are adjusted to reduce the difference between the real output value and the model output. In, [28], stated that “the main purpose of DFNN is to learn an abstract representation of data in a hierarchy by passing the data through multiple transformation layers where each layer has several interconnected processing units”.

4 Results and Discussions

The analysis of this study is divided into three parts. The first part is the comparison between the ARIMA model and ETS. The second part is the comparison between LSTM and DFNN. The third part has to do with the comparison of the two best methods that come out of the first and second parts of the above analysis.

4.1 Comparison between ARIMA and ETS Model

To find out the potential use of ARIMA and ETS models in fitting and forecasting rainfall, the ARIMA model is compared to the ETS model. In this study, it is found that ARIMA (5,0,1) (2,0,0), [12] is suitable to fit the data. The RMSE for the differences between the predicted values from the ARIMA model and the actual values of rainfall for the test data is calculated. The value of RMSE is **38.06956**. The ETS model was built and the RMSE between actual values for variable rainfall in test data and forecast values found from the ETS model was calculated. RMSE in this case is **33.89779**. The RMSE and other performance metric values for both the ARIMA and ETS models are shown in Table 1.

Table 1. Root means square error (RMSE) and other performance metrics for ARIMA and ETS model

	ARIMA model	**ETS model**
RMSE	38.06956	33.89779
MAPE	0.8115115	0.7225838
MPE	72.6696	60.28623
MASE	-0.001548048	0.07732933

A comparison between the ARIMA model and the ETS model for rainfall was made. It was found that the RMSE value for the ARIMA model is higher than the ETS model respectively **38.06956**. Also, if we have a look at the other metrics shown in Table 1, for the ARIMA model, they are in larger values than for the ETS model proving a bigger error in prediction. Therefore, it could be concluded that the ETS model can predict rainfall better than the ARIMA model.

4.2 Comparison between LSTM and DFNN Model

In this part, we will see which of the two deep learning models, LSTM or DFNN is best to forecast rainfalls. We have calculated data points and then divided them into three sets, the training set (from January 1901 to December 2016), the validation set (from January 2017 to December 2019), and the test set (from January 2020 to December 2022) and also followed the steps mentioned in the previous paragraph "Data analysis". We have used 2 horizons, 6 and 12 months, and 12, 18, and 24 lags for each horizon. As a result, we evaluated 6 cases for each model:

– (LSTM and DFNN) 12-1024-512-256-256-6
– (LSTM and DFNN) 18-1024-512-256-256-12
– (LSTM and DFNN) 24-1024-512-256-256-6
– (LSTM and DFNN) 12-1024-512-256-256-12
– (LSTM and DFNN) 18-1024-512-256-256-6
– (LSTM and DFNN) 24-1024-512-256-256-12

After evaluating the results for the LSTM algorithm, the best LSTM model is **LSTM 12-1024-512-256-256-6** based on the average RMSE value, **55.234002** shown in Figure 2, for lag 12 and horizon 6.

As for the DFNN algorithm, **DFNN 24-1024-512-256-256-6** is better than other cases based on the average RMSE value, of **53.723089.** Depending on the horizon of each model, for horizon 6 the best model is **DFNN 24-1024-512-256-256-6** and for horizon 12 the best model is **DFNN 24-1024-512-256-256-12.** These results are also illustrated in Figure 2 and Figure 3. Based on the value of RMSE, the best deep learning model between the LSTM model or DFNN model to forecast rainfalls in Albania, is DFNN with horizon 6, lags 24.

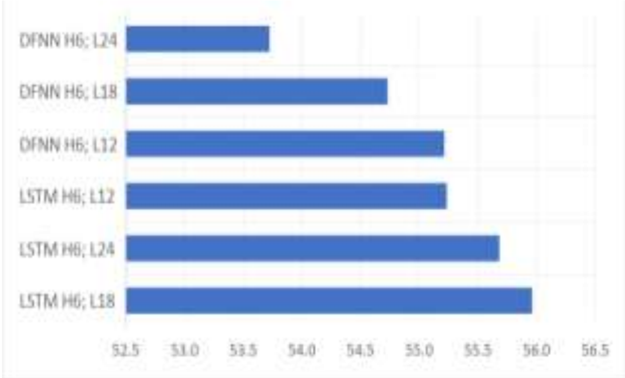

Fig. 2: DFNN and LSTM model ranking for forecasting rainfalls based on the lowest RMSE at h=6

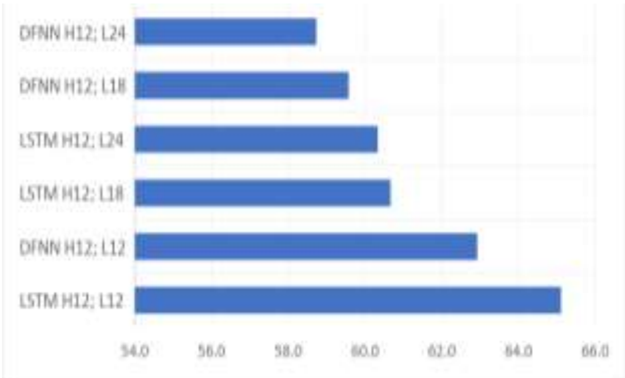

Fig. 3: DFNN and LSTM model ranking for forecasting rainfalls based on the lowest RMSE at h=12

Also, if we evaluate the models by also considering this second part of the analysis to identify those models with the best training and validation loss curves, we will identify by the graphs in Figure 4 and Figure 5 which has the best curve. For the LSTM model, the best training and validation loss curves are **LSTM 12-1024-512-256-256-6**, as shown in Figure 4 below, and for the DFNN model is **DFNN 24-1024-512-256-256-6**, Figure 5.

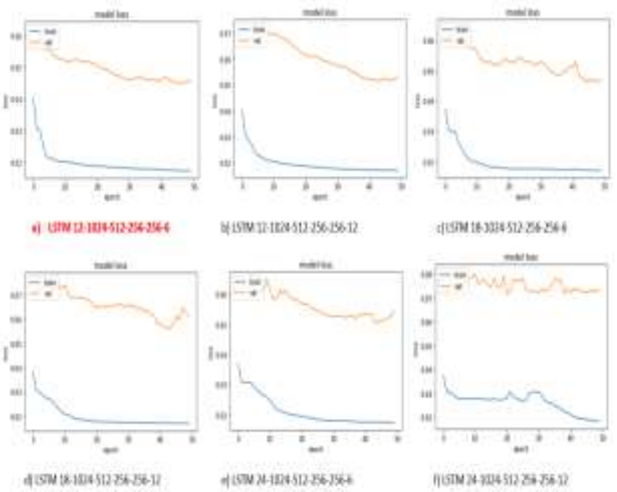
Fig. 4: Training and validation loss for LSTM

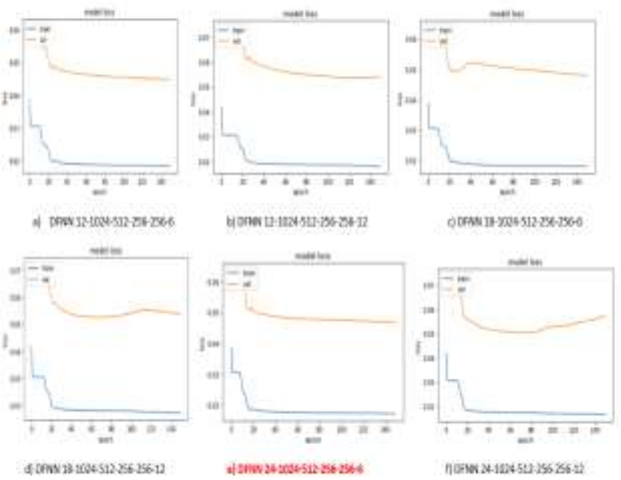
Fig. 5: Training and validation loss for DFNN

So, in conclusion, we can say that we evaluated both algorithms based on the RMSE metric as well as the best training and validation loss curves from these two models where the best model in both comparative cases presented is, **DFNN 24-1024-512-256-256-6.**

4.3 Comparison between ETS and DFNN Model

Based on the results obtained for the two first parts above, where we compared the ARIMA model with the ETS model and the LSTM model with DFNN, we came to the conclusion that the two best models for forecasting based on the RMSE value are ETS and DFNN models. In this paragraph, we will make the final comparison if we will use a machine learning model such as ETS or a deep learning model such as DFNN for the average rainfall variable. We will draw this conclusion based on the performance metrics we have used so far. If we have a look at the RMSE value for the ETS model which is **33.89779** and for the DFNN model which is **53.723089**, we will conclude that the best forecasting model based on the RMSE performance metric is the **ETS model**. If we look at Figure 6 and Figure 7, where the forecast graphs for both models are presented, the ETS model is closer to the real values of the average rainfall time series. This forecast is made for the time interval January 2023 - December 2024. In Figure 7, we have started the values from January 2010 to have a clearer view of the forecast of the values for the years 2023-2024.

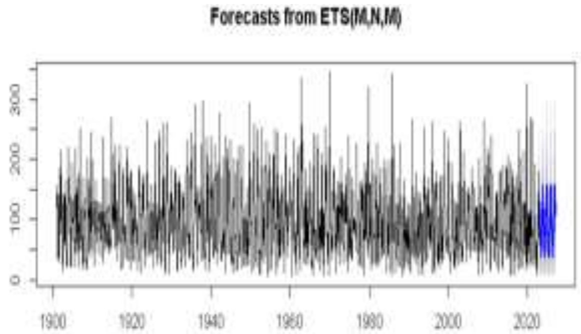

Fig. 6: Plot for test data and predicted values based on the ETS model.

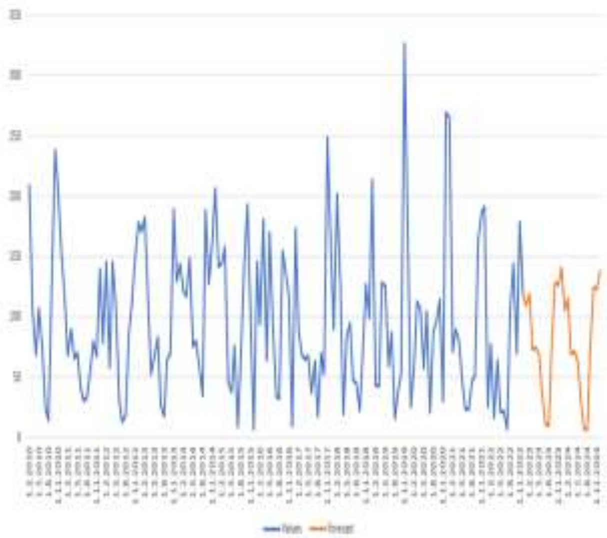
Fig. 7: Plot for test data and predicted values based on DFNN model from 2010

So, using RMSE as the main metric for comparison, we identified that the best forecasting method is ETS. Not only from the metric used but also from the graphic representation of the actual and predicted values above, we see a more accurate forecast for the ETS model.

5 Conclusion

Rainfalls are one of the main climatic elements with a fundamental impact in several different sectors, but in our study, we focused on its effect on agriculture. Since this industry relies on the use of water for its development and maintenance as a whole, the provision of this element becomes a need and necessity. Also taking into consideration the developments and changes in the world economy, where today the focus is moving towards the circular economy, this approach also takes into account water as an element and its use in different industries, but the emphasis in this study is still on agriculture. From the overall information and knowledge, we gained from the literature review, the main idea we formed is that rainfall forecasting plays a key role in maintaining the ecological balance as well as in the sustainable development of various economic sectors, including agriculture, and also plays an important role in the circular economy. Besides the evidence of the importance of rainfall in the aforementioned areas, this study aims to identify the method with the minimum error to guarantee accuracy and efficiency. The methods we used to forecast rainfalls were ARIMA, and ETS as statistical methods and LSTM, and DFNN as deep learning models. The area where we conducted the study is Albania for the period January 1901-December 2022 because of the direct and crucial impact that rainfalls have on our crops. At the end of the study, it is intended to determine the best forecasting technique for this variable. For each model, the corresponding tests were done and the metric used to evaluate the best technique for forecasting as well as to obtain the correct data was RMSE. Also, for the deep learning models we demonstrated training and validation loss curves for each model and evaluated that the best model was the DFNN model with horizon 6 and lags 24. After comparing the RMSE and observing the performance of all methods in the comparison for actual and predicted data, ETS was the one with the best measurements and results. In other words, the obtained results illustrate that the statistical methods optimize the error better than the deep learning models for the dataset for weather collected from World Bank meteorological data. Furthermore, in future work, the comparison between different models can be widened by adding newer algorithms to the existing ones or combining multiple algorithms for better outcomes by using a hybrid method to see how the result would affect the current conclusions we have in this paper. Also, taking into consideration all the variables that affect rainfalls can give the study a different direction of approach.

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