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Comparative Evaluation for Humidity Forecasting Using Deep Learning

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ABSTRACT

Climate change has been well-known in recent years, and it is predicted to continue in the future. Generally, predicting weather has a great effect on citizen's private life in terms of traveling and decreasing disasters. Several research on forecasting humidity over timeframes of minutes, days, months, and years have been undertaken in the last decade. Physical procedures, statistical or hybrid methods, such as neural networks, are the most often utilized strategies for estimating humidity day-ahead, according to a comprehensive set of forecasting methodology. The purpose of this research is to minimize prediction error. Using a recurrent neural network model and Deep Learning. Inthis paper proposed a three methodto evaluate the performance of relative humidity on the bases of deep learning algorithms. The process of prediction has been done based on these three models: Convolution Neural Network(CNN), Long-Short Term Memory (LSTM) model, and hybrid CNN-LSTM model. The researcher has used the real data of humidity for 30 years to train and testing the models.

Keywords—Deep learning, Weather forecasting, LSTM, CNN.

1. Introduction

Weather forecasting uses both science and technology to predict the future state of the atmosphere for a specified location. Quantitative data on the current state of the atmosphere is collected and by using advanced scientific calculations, a model of the atmosphere is created which is used to predict its behavior.

Weather forecasting is often done on supercomputers because the atmosphere's state depends on many elements including humidity, temperature, wind, and rain. The weather deeply affects many areas of life for humans and animals, and so accurate forecasts are essential for many tasks including those related to autonomous vehicles that rely on predicting what the external environment is like. Farming and other outdoor activities rely on accurate weather forecasts as they can be used to predict how the weather affects the ecosystem by changing biodiversity. Dry weather and strong winds can lead to soil erosion, while large temperature changes can affect crops and wildlife.

Extreme weather will impact food security as crop yields are dependent upon the weather, which in turn affects the economy, the health of humans, and how much energy is consumed(Ren et al., 2021),(Cifuentes et al., 2020),(Pratyush Reddy et al., 2020),(Singh & Sahay, 2018).

Many techniques are used in ancient times for weather forecasting such as barometer to tendency, the air force is also used but in the late 19th century, forecasting and analog are both used to predict weather (Center, 2005).Synoptic weather forecasting is used as the first method and was continued till late 1950 (Saxena et al., 2013). Another traditional weather prediction technique was numerical weather prediction (NWP) which was used as a mathematical model of the atmosphere specifically for weather prediction, the statistical approach was the concluding stage of NWP, which specialised in using prior weather to predict forthcoming weather.

Currently, because of the importance of weather forecasting in our daily routine, it is considered a reasonable means in many terms in the world. Lots of researchers are focusing on forecast weather with the use of a machine learning approach(Moosavi et al., 2021). Artificial intelligence (Dewitte et al., 2021), and artificial neural networks have been in use in various meteorological applications(Donadio et al., 2021). Fuzzy logic(Harahap et al., 2021), the approaches of big data analytics in weather forecasting (Fathi et al., 2022).

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In recent years, deep learning(DL) has been utilized in the weather system, and most researchers have used DL in producing the system of artificial intelligence to solve the weather parameters which are nonlinear. DL has been called a satisfactory technique for examining the characteristics of time series. The methods of DL have been widely utilized in atmosphere applications(Schultz et al., 2021) convolutional neural networks (CNN)(Kareem et al., 2021),RNN such as long short-term memory (LSTM) and gated recurrent units (GRU)(Y. Yu et al., 2019)(Chhetri et al., 2020),generative adversarial networks (GAN) a convolutional long short-term memory network (ConvLSTM) (F. Wang et al., 2020)(Sun & Zhao, 2020) are used as methods of DL in terms of meteorological. Since weather is a non-linear analogue phenomenon, ANNs are ideal for modelling non-linear weather patterns.By adding more complications DL shares classical machine learning in neural network model and changes different aims of data using in a layered way within numerous levels of abstraction.

The main aim of this paper is to present using deep learning approaches for weather forecasting. This paper has been organized as follows:in section 2, the literature review. Section 3, discussed deep learning and methods, section 4 presents a result, and the conclusion in section 5.

2. Literature Review

Recently various techniques have been proposed for achieving better accurate weather forecasting by different researchers. In this section, the researcher has tried to present researches that are done regarding deep learning.

In (Qadeer et al., 2021) this investigation for estimating relative humidity (RH) is based on well-proven approaches of machine learning which is a random forest algorithm. A random forest algorithm is a successful approach to predicting air quality parameters, especially RH. So for implementing this approach and solving complex estimation problems, the ASPEN HYSYS process Is used to take out the prediction of RH, this simulator is linked with MATLAB.Random forest model was compared with the support vector machine(SVM) regression model for evaluating the prediction performance RF model. The consequence was that the execution of the RF model was better than the SVM model by 74.4%

The goal of this work(Hutapea et al., 2020) is to show how to evaluate the performance of relative humidity forecasting using anapproach of machine learning which is called long short term memory (LSTM). A dataset produced by a weather station was the basis for an LSTM model to forecast relative humidity. In the synoptic station, a series of relative humidity was recorded, and the model was trained to forecast relative humidity based on time-series from 2008 to 2009. The performance of RH prediction using an LSTM model that can be employed with four distinct time periods, including RH07, RH13, RH18, and RH average, has been analysed. Therefore, machine learning techniques are becoming beneficial for RH prediction, with the LSTM based on time-series records producing acceptable forecasting performance.

(Rizvee et al., 2020)this paper is used machine learning models to predict north-western Bangladesh weather to know the accuracy of the weather prediction in a very short time. To predict, the data of thirty years have been used (from 1986 to 2017): temperature, wind, rain, and humidity. In this study, both artificial neural networks (ANN) and extreme learning machine (ELM) algorithms are used to solve the weather forecasting problem via using measures of MAE and RSME.As the result, the algorithms of ELM are considered better algorithms than ANN algorithms to rainfall, temperature, wind, and humidity based on using the same results of RSME, MAE, MASE, PP, CC prototypes.

Using the convolutional neural network (CNN) with Bi-directional long short term memory (BI-LSTM) networks in(R. Wang, 2018)for the purpose of predicting the problem of multivariable nonlinear time series, also comparing the performance of CONV-BI-LSTM and LSTM model in multi-step prediction. The dataset consists of many weather parameters such as temperature and humidity… etc. It has been taken from the meteorological station in Beijing. As the result, the performance of the Conv-Bi-LSTM model is much better than a single LSTM model for both parameters of weather such as humidity and temperature.

The deep learning algorithm is a very important associate in developing weather prediction(Fu et al., 2019). In this study, two algorithms of deep learning as a hybrid model are used for weather prediction which is 1D CNN (1-Dimensional Convolution) and Bi-LSTM (Bidirectional Long Short-Term Memory). Bi-LSTM and 1D-CNN are applied to predict three parameters of weather that are the 2-m temperature, 2-m relative humidity, and 10-m wind speed. For this purpose, the researchers have used ”OBS” and ”RMAPS” datasets. The experiment results can simply clarify the comparison between the FNN model using 1D-CNN, LSTM, and BI-LSTM algorithms with the suggested hybrid model which was based on 1D-CNN and Bi-LSTM will have a very greater performance in predicting the weather. additionally, One-hot encoding improved the accuracy of weather forecasting models in unknown neighbourhoods.

(Sri Rahayu et al., 2020)this study is to estimate temperature for the following three days utilizing fiveclassifications,namely "Cold," "Cool," "Normal," "Warm" and "Hot" as well as other meteorological characteristics such as temperature, humidity, rainfall, and wind speed from 2000 to 2019. For the previous 20 years, data has been

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collected from the Bureau of Meteorology, Climatology, and Geophysics (BMKG) in Bandung. There are used RNN and LSTM models for predicting weather parameters, also interpolation, feature extraction, normalization, and segmentation are used to process pre-processing data as input data. The accuracy applying Adam's optimization model which the number of epoch is equal to 100 in the training data was 90.92 percent, while the accuracy in the test data was 80.36 percent. As a result, the optimization model, the amount of data, and data sharing can all have an impact on the final outcomes.

Establishing a novel ensemble model for multi-step ahead electric load forecasting based on two algorithms which are: vibrational mode decomposition (VMD) and extreme learning machine (ELM) in this research (Lin et al., 2017). The datasets are collected from New South Wales (NSW) and Queensland (QLD) in the Australian electricity market.

The experimental results produced three outcomes. The first being, the proposed forecasting model produced more accurate results when compared to both one-step and multi-step ahead electric load forecasting. The second outcome was that the errors produced by ELM was substantially less than the errors generated by VMD. Finally, the DE algorithm, introduced to improve the thresholds and the initial weights, enhanced the ELM model's forecasting performance.

This work(Karevan & Suykens, 2020) uses LSTM to create a data-driven forecasting model for a weather forecasting application. Furthermore, we offer T-LSTM (Transductive LSTM), which uses local information in timeseries estimation. from the Weather Underground website, data has been collected and weather parameters such as minimum and maximum temperature. The results imply that transductive LSTM outperforms LSTM in many circumstances when varied sequence lengths and transfer functions are used. More, despite minimal data, the inductive and transductive LSTM models as data-driven approaches are demonstrated to be comparable with state-of-the-art weather forecasting systems. As a result, the inductive LSTM model performs better in November and December than it did in April and May.

The aim of (Hewage et al., 2021) is to progress and estimate the novel–weight, data-driven weather forecasting model by LSTM (long short term memory) and temporal convolutional networks (TCN). Meanwhile, comparing performance with classical machine learning approaches like standard regression (SR), Support vector regression (SVR), Random Forest (RF), statistical forecasting models such as Autoregressive Integrated Moving Average (ARIMA), Vector Auto Regression (VAR), and Vector Error Correction Model (VECM), and a dynamic ensemble method which is Arbitrage of Forecasting Expert (AFE). The utilize of the proposed neural network model for short-term weather predictions and comparing the outcomes with WRF model forecasting. The WRF model is conducted using GRIB data. Between January and May 2018, a total of 12 weather variables were retrieved. As a result, when compared to MIMO, the MISO technique yields better MSE values. In contrast to the LSTM, the Bi-LSTM delivered increased precision in extended forecasts. Thus higher precision can be obtained by using Bi-LSTM. In general, the deep learning model conveys enhanced prediction when equated to the WRF model for up to 12 hours.

The goal of(Priyanka et al., 2021) is to introduce a framework of the novel to automatically take out this information from street-level images regarding weather and visual conditions like dusk/dawn, night and day for detection of time, the glare of lighting conditions, foggy, clear, snowy and rainy for the conditions of weather depending on. The researcher has collected different datasources from Kaggle by using CNN (Convolutional Neural Network) which is a so-called weather net. As the result, the weather net which is proposed has shown a strong performance in realizing the categories of different combinations of an image on deep learning and computer vision.

The purpose of this work (Et.al, 2021) is to implement a new hybrid machine learning strategy to accurately predict the status of rainfall: The methodology that is proposed is called Intense Neural Network Mining (INNM). the method of INNM explains the prediction of rainfall scenarios depending on two different logics of machine learning which are the Back Propagation Neural Network and the Rapid Miner. A novel data set has been used in the studier from the Regional Meteorological Centre Chennai. As a result,the prospective proposition of INNM results in a precision of approximately 96.5%in forecasting with a base error rate of 0.04%and the subsequent sections of this paper presents solid confirmation of this conclusion in a graphical procedure. The weather prediction is based on a neural network (Hemalatha et al., 2021). For weather data classification a fully associated neural network (FCNN) is suggested. The researchers at the Indian Meteorological Department (IMD) collected substantial amount of data. The values of samples are “Temperature”, “dew point”, “humidity”, “wind type”, “wind speed”, “wind gust”, and “pressure”. As a result, FCNN model performance is much higher compared to fine gaussian SVM (FGs) in some different meters such as UA, PA, and KC.Table 1 summarises some of the papers used in the literature review.

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3. Methodology

3.1. Deep learning

Deep learning is considered a brand of machine learning which is based on multi-layered artificial neural networks. Deep learning is also considered a framework of mathematics for the purpose of learning representations of data. It focuses on learning from levels that are successive. These ranked symbols are almost always learned through neural network models.

One particularly fruitful concept, which has been extensively applied, is convolutional neural networks (CNN)(Alzubaidi et al., 2021). The more advanced RNN architectures are the followings: long short-term memory (LSTM)(Staudemeyer & Morris, 2019), and gated recurrent units (GRU) (Dey & Salem, 2017)which both are able to be embedded in more intense neural network architectures. For instance, the combination of LSTM and CNN are potential to produce a so-called ConvLSTM(Islam et al., 2020) network. The two updated concepts of DL are variational auto-encoders (VAE)(Thin et al., 2021)and generative adversarial networks (GAN)(Gonog & Zhou, 2019). Both of them are considered so-called generative models, Conditional Restricted Boltzmann Machines(CRBMs)(Salman et al., 2016), and capsule neural net (CapsNet)(Ren et al., 2021) which are two other algorithms of deep learning.

Deep learning is the most important branch of machine learning. As the most crucial branch of machine learning, Dl has been quickly developed in recent years and has been useful for many different fields such as: natural linguistic programming (Lauriola et al., 2022),computer vision (Voulodimos et al., 2018) and speech recognition

(Lee et al., 2021), and Deep learning has also been used in many natural science fields which are: chemistry(Korshunova et al., 2021), physics (Tanaka et al., 2021) and bio information(Jin et al., 2021).

DL based weather prediction (DLWP) has appeared in several contrasting subjects, including agronomy. (Chen et al., 2019), the authoritative meteorological research institution ECMWF and parameterization of ocean physics(Dueben & Bauer, 2018), as well as the school journal Nature(Reichstein et al., 2019) and creativities, e.g. Alibaba Group (Qiu et al., 2017) and Google Research (Sønderby et al., 2020).

3.2. LSTM

A special type of RNN is long short-term memory (LSTM). The aim is developing the memory of RNN of the past by putting it into practice to recall the crucial stuff and neglect the rest.

In each input, LSTM is able to manage memory by using cell memory or gate unites in neurons. Each neuron has three different gates which are: Forget gate, Output gate and input gate(Prediction, 1967).

The gates within the neurons regulates the memory, input and output values as shown in Fig 1.

Each LSTM network creates two-cell state values which are combined with output values to produce new input values for depositing into interim memory.Additionally, in LSTM, memory is named as cells which take inputs from the former state (h_{t-1})and recent input (X_t).

Deletion and storage of data within the memory is carried out by the group of cells (Sri Rahayu et al., 2020).

To produce weather predictions, the proposed model is based on the networks of LSTM and time-series weather data has been used. Thirty years of humidity data is used as the input for the proposed model.The number of neurons of LSTM layer which have been used for this model is 50 neurons and Relu function is used as activation function which its duty is changing data into a range (0-x).(Prediction, 1967). After giving the input to the model, the first step in which LSTM will implement in forget data is deciding on which information will not be remaining in cell state.

After that, the model will decide on saving new information and this action takes two parts which are input gate and update cell state: the duty of input gate is determining the value to save them and the duty of update cell state is determining a new cell candidate with using activation function tanh.

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Table 1. The comparison between paper reviews

Authors	Purpose	Dataset	Method	Result
(Jin et al. 2020)	Predicting the problem of multivariable nonlinear time series, Comparing the performance of the CONV-BI-LSTM and LSTM model in multi-step prediction.	Meteorological station in Beijing, parameters (temperature and humidity)	CONV-BI-LSTM LSTM	RMSE(RH) of CONV-BI-LSTM = 14.11 RMSE (RH)of LSTM =15.32 RMSE (T)of CONV-BI-LSTM =2.47 The RMSE (T)of LSTM=3.21
(Rizvee et al. 2020)	Using machine learning models to predict north-western Bangladesh weather to know the accuracy of the weather prediction in a very short time.	Bangladesh meteorological department (BMD).	ANN ELM	ELM provides a 95% accuracy and a 70% high-performance rate rather than the ANN algorithm
(Hutapea et al. 2020)	evaluate the performance of relative humidity prediction using a machine learning approach.	the Indonesia Meteorology from synoptic (9601) Station location.	LSTM	predicting of RH for training detail score = 0.46 predicting of RH for testing detail score=0.40
(Fu et al. 2019)	A hybrid model combing 1D-CNN and Bi-LSTM is used to enhance the accuracy of the weather forecasting.	OBS RMAPS dataset	1D-CNN Bi-LSTM LSTM FNN 1D-CNN+LSTM 1D-CNN+Bi-LSTM	1D-CNN + Bi-LSTM in average-62 score =0.4248 FNN=0.3411 1D-CNN=0.4011 LSTM=0.4019 Bi-LSTM =0.4120 1D-CNN + LSTM=0.4062
(Rahayu et al.2020)	Estimate temperature for the following three days utilizing five classifications, namely "Cold," "Cool," "Normal," "Warm," and "Hot,"	Meteorology Climatology and Geophysics Agency (BMKG) in Bandung for the past 20 years.	RNN LSTM	The accuracy of Adam's optimization model in the training data=90.92% The accuracy of Adam's optimization model in the testing data= 80.36% The accuracy of SGD in training data =87.24% The accuracy of SGD in testing data=76.48%
(Sakthivel et al. 2021)	New hybrid machine learning technique to predict rainfall to save human life against natural disasters.	Regional Meteorological Centre Chennai (C-RMC)	INNM BPNN and RM	rainfall data prediction with good accuracy level=96.5% lowest error ratio =0.04%
(Hemalatha et al., 2021)	Prediction of weather based on a neural networks by applying FCNN model	Indian metrological Department (IMD)	FCNN FGS	FCNN(%) for class1(UA=85.45,PA=71.48) Class6(UA=92.74,PA=96.46) KC=0.945 FGS(%) for class1 (UA=79.63, PA=68.24) Class6(UA=89.14, PA=92.46) KC=0.867

The model's final layer, the dense layer, has a single output. For training, the batch size is 256, the learning rate is 0.0003 and the training runs for 100 epochs.

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3.3.CNN

The neurons of human and animal brain are the inspiration for the structure of CNN which is highly close to conventional neural network.

The main usage of CNN is the automation of identifying the available features without the need of human supervision which this is not available with its predecessors(Zhang et al., 2019). CNN has been intensively applied in many different fields such as speed processing(Alzubaidi et al., 2021), computer vision and face recognition (Zhang et al., 2019).

CNN have a great performance and its excellency in performance has been seen in many various applications like image classification, medical image analysis(H. Yu et al., 2021) and object detection(Yanagisawa et al., 2018), A CNN is included of three layers with convolutional, pooling, and fully connected(Altaf et al., 2019). Such kernels are convolving an entire input via using "stride(s)" in which the dimensions of an output volume increase to integers(Khan et al., 2020) . The dimensions of an input volume lower down when the convolutional layer is utilized to do the process of striding that is shown in Fig.2 .

50

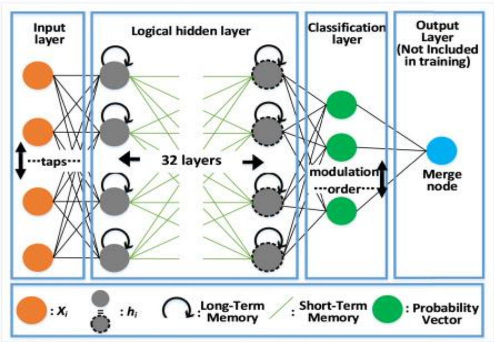

Fig.1 structure of LSTM model

For the purpose of reducing the number of parameters, the Pooling layer is performing down the sampling of a given input. The most common method can be max-pooling which creates the highest value in an input region. The fully connected layer is working as a classifier to decide on the basis of features which are taken from the pooling layer and convolutional(Islam et al., 2020).

In various metrological predictions, convolutional neural is used. CNN can also be useful for thrilling weather forecasting. We have tried to predict the humidity by using CNN model. The network is designed in a way which the kernel numbers to 1D convolutional is 64. Also to train data, the kernel size is mostly 2, then max-pooling action will be implemented on it and the output which is produced from this layer will be flatten. After the action of flattening, the output layer predicts humidity by using 50 neurons in the Relu activation function.

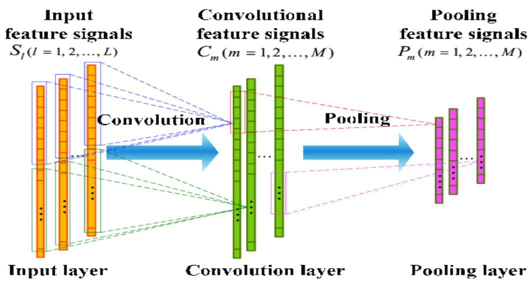

Fig.2 structure of CNN model

3.4.Hybrid CNN_LSTM model

By joining CNN and LSTM networks, the structure of CNN-LSTM was created in which CNN is used before LSTM layer to take out the complex features in time series data(Li et al., 2020). LSTM is working with Dense layer as a classifier on the output that has been shown in Fig.3.

Surely, before designing the model, the samples and features must be reshaped. The proposed model is used to predict humidity which the network structure has been created based on this. CNN model has been introduced with 1 D

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convolutional with 64 kernel. Moreover, the kernel size network is used with using activation function Relu and dimensions of input max-pooling size =2.

50 neurons have been used to LSTM layer with one output to dense layer. Generally, the model is the convolutional layer which fully connected and one LSTM layer also Dense layer.

4. Result and Discussion

The weather data set which is used to implement the models is humidity dataset from Erbil for 30 years. firstly, the data set was divided to train and validation set and the data scale turned to min-max normalizations, the same dataset has been used to train all the three models. Adaptive moment estimation (ADAM) by using 100 epochs to train the models, learning rate =0.003 and batch size is 256.

To determine the performance of relative humidity RMSE (root mean square error) has been used to detect the best performance in choosing the best model.

Comparing the prediction train and validation to LSTM, CNN, and Hybrid CNN-LSTM models which has been shown in Figures 4,5, and 6.

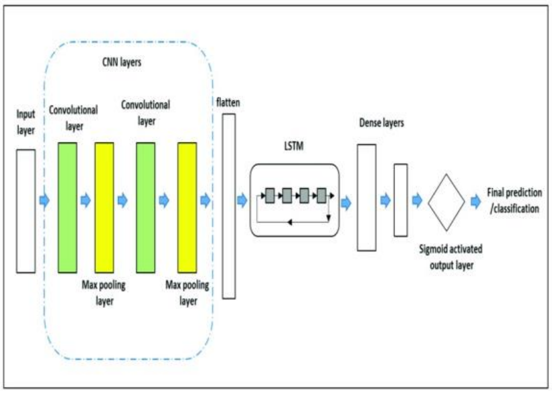

Fig.3 structure of Hybrid CNN-LSTM model

Table 2: performance LSTM model for train and validation

Train		**Validation**	
Month	**RMSE**	**Month**	**RMSE**
Jan	0.1038	**Jan**	0.05737
Feb	0.2259	**Feb**	0.12342
Mar	0.4785	**Mar**	0.09371
Apr	0.6248	**Apr**	0.11526
May	0.4069	**May**	0.06362
Jun	0.5369	**Jun**	0.21793
Jul	0.5369	**Jul**	0.21793
Aug	0.4378	**Aug**	0.24071
Sep	0.4442	**Sep**	0.25534
Oct	0.4237	**Oct**	0.14328
Nov	0.2235	**Nov**	0.18269
Dec	0.093	**Dec**	0.07205

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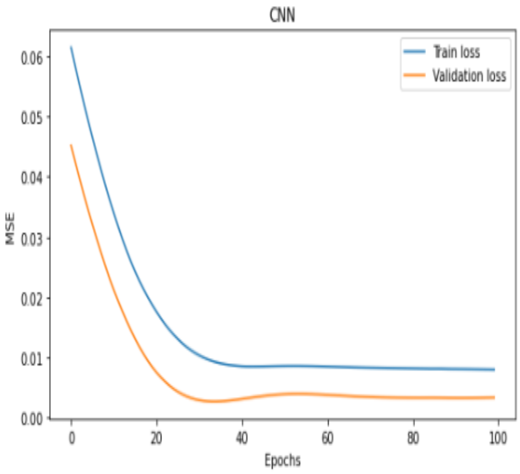

Fig.4 : CNN model prediction

Table 4 shows the result of the performance of these three models which has been utilized to predict humidity dataset for 30 years which has been taken from the real dataset of Erbil to evaluated and compare LSTM, CNN and hybrid CNN-LSTM model for weather prediction.

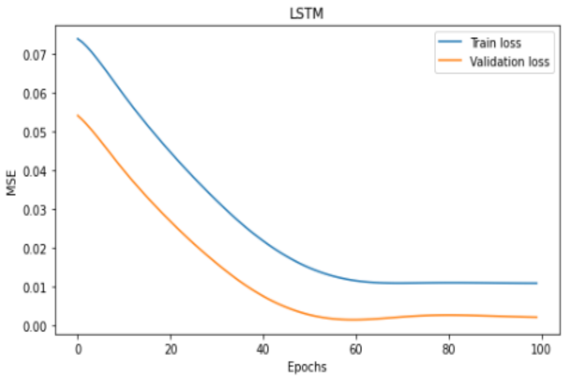

Fig.5: LSTM model prediction

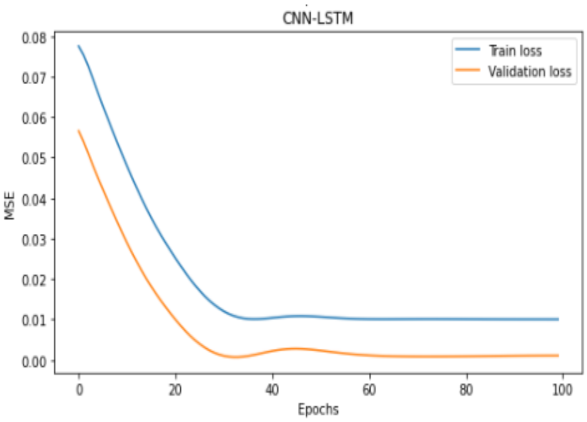

Fig.6: CNN_LSTM model prediction

Table3: performance CNN model

Train		**Validation**	
Month	**RMSE**	**Month**	**RMSE**
Jan	0.0892	**Jan**	0.0574
Feb	0.0478	**Feb**	0.1234
Mar	0.1648	**Mar**	0.0937
Apr	0.2967	**Apr**	0.1153
May	0.1011	**May**	0.0636
Jun	0.1898	**Jun**	0.2179
Jul	0.1898	**Jul**	0.2179
Aug	0.2173	**Aug**	0.2407
Sep	0.1856	**Sep**	0.2553
Oct	0.0987	**Oct**	0.1433
Nov	0.0684	**Nov**	0.1827
Dec	0.0333	**Dec**	0.0721

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RMSE metric has been used for the purpose of performance the models that has been used: the compare was the performance of LSTM model for training and validation for whole 12 months of year which has been shown in table 2. Meanwhile, the performance of CNN model and Hybrid CNN-LSTM was for training and validation which has been shown in Tables 3 and 4.

Table 5: performance of LSTM ,CNN and CNN-LSTM for 30 years

RMSE	RH(validation)	RH(train)
LSTM	0.1486	0.378
CNN	0.1486	0.1402
CNN-LSTM	0.2255	0.2504

After calculating the average of the mentioned method for the training and validation section as shown in table 5. The result present that the CNN is better than the mentioned methods. The goal of the hybrid in this paper to decrease the RMSE for LSTM to detect the good result compared with the LSTM.

5. Conclusion

This paper is trying to use a system of algorithms of deep learning to predict the important parameters of weather which is relative humidity or on the dataset which has been collected for 30 years in Erbil. In general, The machine learning techniques are verifying useful for predicting relative humidity as data forecasting.

The models which are used for weather forecasting are based on LSTM, CNN and combined CNN and LSTM model which all have been applied on the same dataset. On another hand, another goal of this work is evaluating and comparing between the models that are participating in relative humidity prediction. Moreover, to do this job, three main steps are needed: The data is preprocessed by using min-max normalization, while the model is a CNN-LSTM hybrid, and finally the model is tested by using test data.

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