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Research Article

A Deep auto-encoder based Framework for efficient weather forecasting

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Abstract:

Weather forecasting has a plethora of benefits in different domains. Traditional weather forecasting approaches apply science and technology to predict weather conditions in a given place and time. With the emergence of artificial intelligence (AI), there are increased possibilities for weather forecasting research. Instead of ground-level observations, AI approaches learn from historical and current atmospheric data to develop predictions. We suggested a framework for autonomous weather forecasting based on deep learning. Our framework is a variant of the Convolutional Neural Network (CNN) model, which exploits the encoder and decoder to learn parameterizations from the given data and forecast weather. The proposed model can interpret spatial information associated with geopotential fields and automatically infers forecasting know-how with higher accuracy levels. A variable selection process is incorporated to determine geopotential height that impacts the weather conditions. We proposed an algorithm called Deep Weather Forecasting (DWF) to realize the proposed framework. Our empirical study has revealed that the proposed framework evaluates different deep learning models and compares their performance. Our deep learning models outperformed many existing regression models. U-Net showed the highest performance with the least MAE, 0.2268, compared to all other models.

1. Introduction

There are many fields whose operations are determined based on weather conditions. Agriculture is one such field that is influenced much by weather forecasting. In the same fashion, aviation, fishing, and transportation, to mention a few, depend on weather conditions. It can be seen that different methods deal with weather conditions[1-5]. Time-series data analysis-based and forecasting methods. With the emergence of AI, there has been increased research in deep learning techniques suitable for processing large volumes of data to arrive at forecasting decisions. As reported in deep learning modes are widely used for weather forecasting [1,2,3,6]. CNN is the model that has been found suitable for dealing with weather datasets. From the literature, it is observed that there are statistical methods and also deep approaches to forecasting weather. Traditional regression models or ML models are found in [1,4,7-13]. These models perform regression on the given data to arrive at a forecast. Regression models are ideal for forecasting weather instead of classification models. There are many CNN-based models found in the literature on weather forecasting. Traditional CNN models are widely used to solve problems in real-world applications. They are mainly used for classification tasks. However, there is a need for a framework that exploits encoder and decoder architecture with CNN variants. We have made the following contributions to this paper:

- We proposed a deep learning-based framework for automatic weather forecasting. Our framework is a variant of the Convolutional Neural Network (CNN) model, which exploits the encoder and decoder to learn parameterizations from the given data and forecast weather.
- We proposed a Deep Weather Forecasting (DWF) algorithm to realize the proposed framework.
- We built an application that takes a dataset from and exploits a pipeline of deep learning models for automatic weather forecasting and evaluation of the proposed framework.

The rest of the paper is organized as follows: Section 2 discusses the findings of the literature. Section 3 presents a proposed framework for automatic weather forecasting. Section 4 shows the results of the experiments. Section 5 concludes our work and provides a future score.

2. Related Works

This section reviews the literature on existing deep-learning models used for weather forecasting. Zeelan et al. [1] explored ML and DL techniques for rainfall detection. Huaizhi et al. [2] used deep learning for forecasting energy consumption concerning renewable energy. Kanghui et al. [3] investigated different weather forecasting approaches using learning-based architectures. Zhao et al. [4] proposed a methodology based on a point prediction approach with short-term predictions using ML techniques. Nath et al. [5] combined deep learning models and statistics-based methods to arrive at accurate pollution forecasts. Thors et al. [6] used satellite images to analyze them using deep architectures and predict the possibility of cyclones. Abed et al. [7] used SDO images for their experiments. Using profound learning advancements, they achieved automatic forecasting of solar flares. Canar et al. [8] defined a model based on deep learning towards statistical weather forecasts associated with a city in Quito. Qi et al. [9] studied the air quality index and its forecasting possibilities. Towards this end, they proposed a DL model to forecast air index. Haiwen et al. [10] proposed a hybrid method that combines a deep neural network and sparse coding approach toward forecasting day-ahead weather.

Pang et al. [11] explored a data-driven approach using Bayesian DL to know whether there are irregularities in a given geographical region. Wang et al. [12] considered two aspects such as wind power and wind speed forecasting using DL techniques. Ahmad et al. [13] used sky videos to experiment with solar irradiance forecasting using deep architectures. Kanishk and Sudip [14] used videos about floods and proposed a DL model to detect the severity of flood levels. Using their approach, Zhang et al. [15] investigated deep learning models for real-time wind field forecasts and bias correction. Other significant contributions include short-term forecast models [16], IoT-based models [17], forecasting solar radio flux [18], CNN+LSTM [19], and Forecast for Grids [20]. The existing methods showed different means of predicting the weather. However, there is a need for a framework that exploits encoder and decoder architecture with CNN variants. Similar works has been done and reported [21-25].

3. Materials and Methods

The dataset used in this paper is collected from [26]. It is the benchmark dataset used for global climate analysis. Because the data contains many attributes, we used output variables such as total precipitation and geopotential height. Figure 1 shows the details of the study area.

As presented in Figure 1, a subset of available data is chosen for empirical study. Our experiments used a simple reference model and three CNN-based encoder decoder architectures. These deep-learning models are used for experiments per the pipeline in Figure 2. It has two essential parts, such as variable selection and training. The provided dataset has 80% training and 20% test sets. This data is used for training and prediction, respectively. The variable selection process is used to find fields that contribute to accurate weather prediction. The chosen variables are then given to train deep learning models like VGG-16, U-Net, and Segnet. Each of these models is based on the encoder and decoder architecture. The deep learning models are configured to perform regression and are used for weather forecasting. The three models are trained with the 80% training set. The number of epochs used for experiments is 50. The optimizer's learning rate is set to 0.01 and configured using Stochastic Gradient Descent (SGD). Mean Square Error (MAE) is the loss function used to assess performance. The models are implemented using Keras and TensorFlow.

As presented in Figure 3, the VGG-16 model is provided with an encoder and decoder architecture. It is configured to perform regression of the test data and provide weather prediction results. This kind of architecture is widely used with CNN variants. As found in the literature, the model is suitable for forecasting. This kind of architecture is configured for each deep-learning model. In the process, a correlation function is computed as in Eq. 1.

$$C2(q,t_1,t_2) = \frac{\langle I(q,t_1)I(q,t_2)\rangle}{\langle I(q,t_1)\rangle\langle I(q,t_2)\rangle} \quad (1)$$

It has many time and vector components. The encoder's idea is to reduce the input size by transforming it into a lighter representation. When there is a reconstruction process in decoding, there is a provision for finding future possibilities or forecasting. The dynamics of Eq. 1 can be approximated as in Eq. 2.

$$C1(q,\delta t) = C_\infty + \beta|f(q,\delta t)|^2 \quad (2)$$

The correlation process can be further approximated as in Eq. 3.

$$C1(q,t) = C_\infty + \beta e^{-2(\Gamma t)^\alpha} \quad (3)$$

The model training with 80% of the training data helps the deep learning models learn from the data.

Algorithm: Deep Weather Forecasting (DWF)
Input:
Global climate analysis dataset D
deep learning models pipeline M (U-Net, Segnet, VGG-16)

Output:
Forecasting results R, performance statistics P

1. Begin
   Data Preparation for Training and Validation
2. (T1, T2)←DataSplit(D)
3. F←VariableSelection(D)
   Training
4. For each model m in the pipeline M
5. E←Encoding(m,T1)
6. D←Decoding(E)
7. Save model m
8. End For
   Forecasting
9. For each model m in the pipeline M
10. R←Forecast(m, T2)
11. P←Evaluate(m,R)
12. Display R
13. Display P
14. End for
15. End

Algorithm 1: Deep Weather Forecasting (DWF)

They also perform specific regression processes with deep learning using encoder and decoder architecture. The proposed models provide better results than traditional regression models. As presented in Algorithm 1, it takes Global climate analysis dataset D and deep learning models pipeline M (U-Net, Segnet, VGG-16) as input. It provides output in Forecasting Results R and performance statistics P. The algorithm splits the given dataset D into a training set, T1, and a test set, T2. Then, iterative processes train all the models in the pipeline and forecast with all the trained models, resulting in forecasting details and performance statistics.

4. Experimental Results

Experiments are made with the proposed framework. Concerning variable selection, some geographical height levels are determined for better quality in the training data. A simple encoder and decoder model is trained 175 times. Different deep-learning models are used for performance evaluation. MAE is the metric used for performance evaluation.

2. Material and Methods

As presented in Figure 4, lower levels of the atmosphere provide better estimates than their higher-level counterparts. Lower levels showed fewer MAE values, reflecting higher prediction performance. As presented in Figure 5, deep learning models with encoders and decoders are used for empirical study. All of them are executed with 50 epochs. The simple model has 745000 parameters and took 0.7 hours to train. The VGG-16 model has 1646749 parameters and needs 3.9 hours. The Segnet model has 29458957 parameters and took 7.5 hours. The U-net model has 7858445 parameters and took 2 hours to train. The results show that the number of parameters influences the time taken. As presented in Figure 6, the performance of all deep learning models is provided against different epochs. As the number of epochs increases, the MAE gradually decreases for all the models. Model loss is the metric used for error rate. A low loss value indicates better performance. Therefore, the U-Net model is outperforming all deep models. As presented in Figure 7, the MAE value is used to compare different prediction models. The simple model showed 0.2975, VGG-16 0.2528, Segnet 0.2511, and U-Net 0.2268. The U-Net model achieves the lease MAE value, reflecting the highest performance.

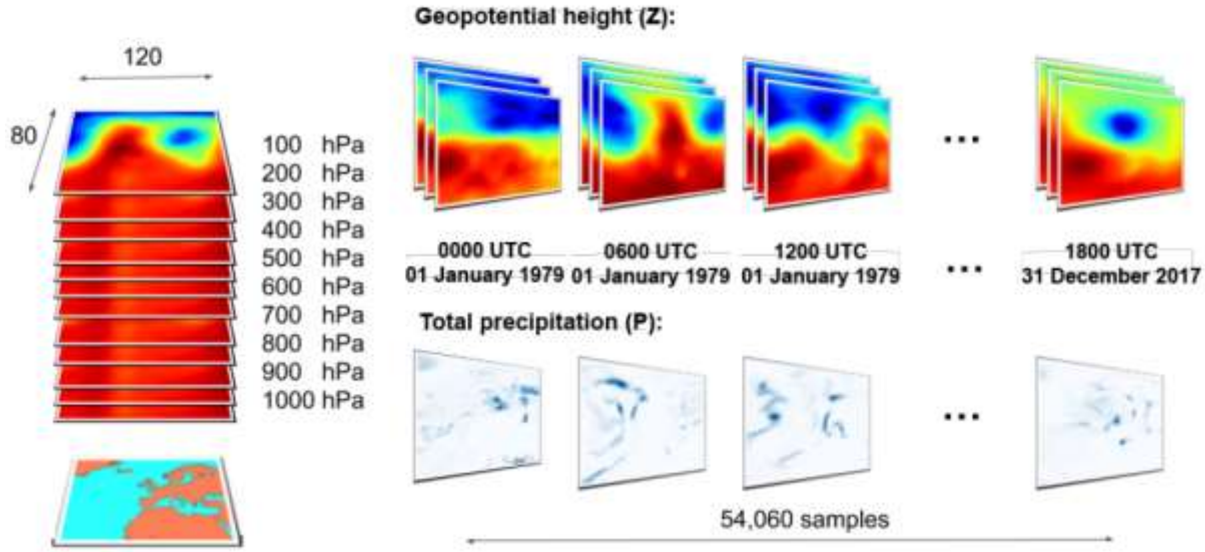

Figure 1. *Illustrates the study area with longitude (-50, 40) and latitude (75, 15)*

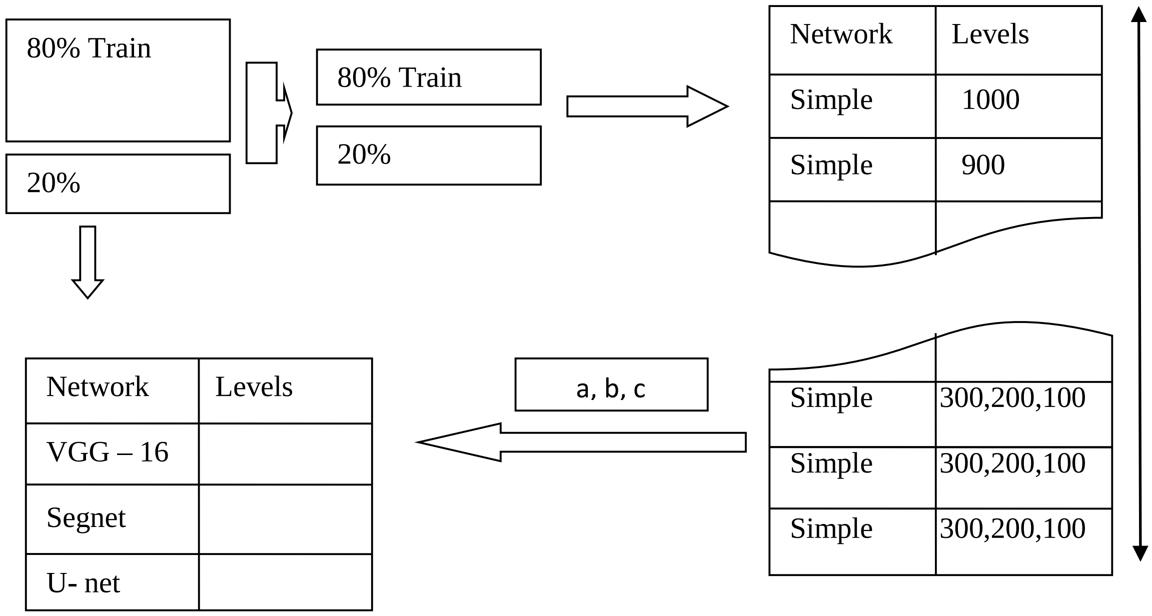

Figure 2. *Outline of the proposed experimental pipeline*

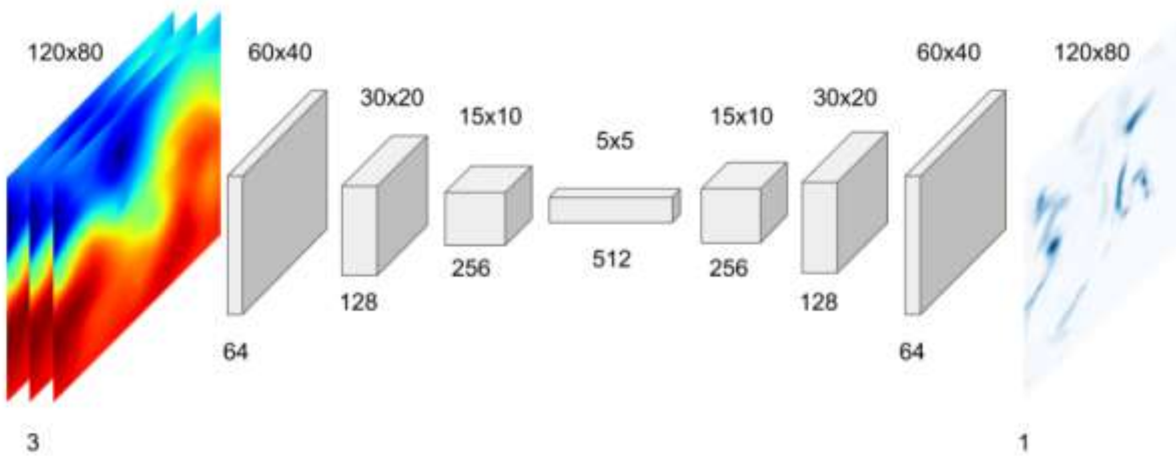

Figure 3. *VGG-16 model with encoder and decoder for weather forecasting*

As presented in Figure 8, the MAE value is also used to compare different prediction models. Like the linear regression model, ML models showed 0.4054 MAE, Lasso 0.4035, and RF 0.3953. Deep learning models such as the Simple model showed 0.2975, VGG-16 0.2528, Segment 0.2511, and U-Net 0.2268. The U-Net model achieves the lease MAE value, reflecting the highest performance.

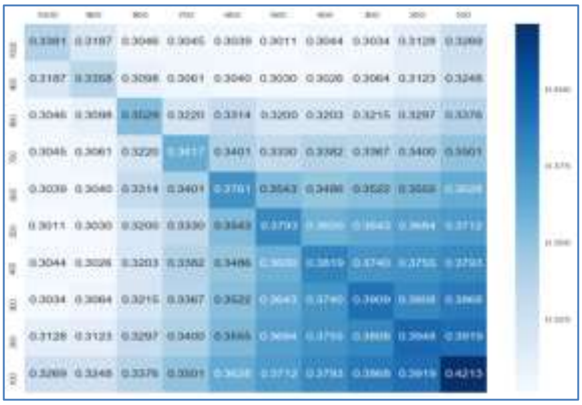

Figure 4. *Shows matrix reflecting MAE values due to training with geopotential level*

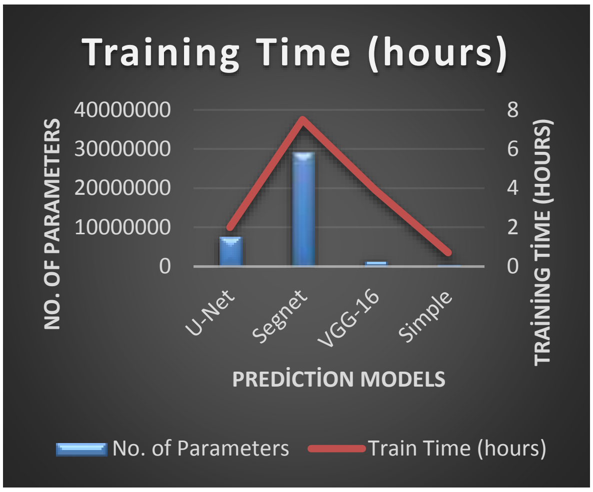

Figure 5. *The deep learning models and their training time dynamics*

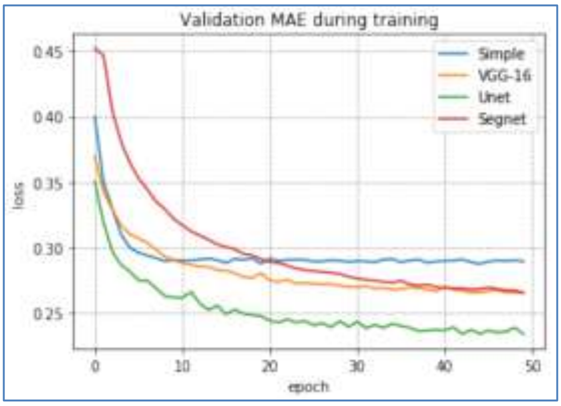

Figure 6. *Performance of deep learning models in terms of MAE*

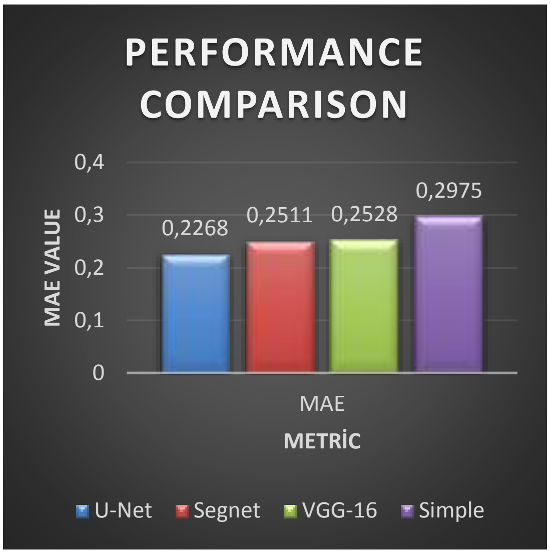

Figure 7. *Performance comparison of all deep models*

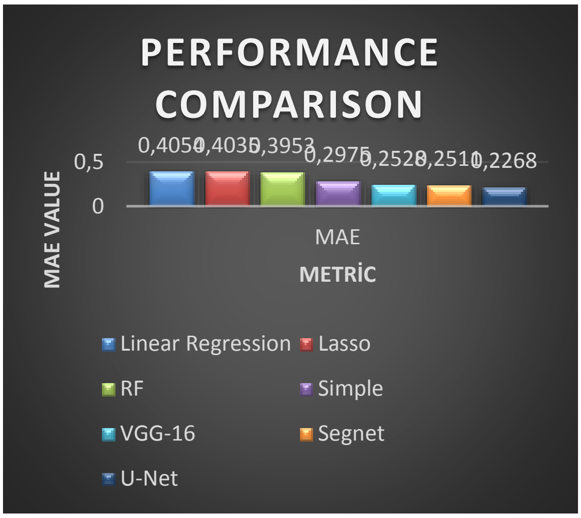

Figure 8. *Performance comparison among ML and deep learning models*

4. Conclusions

This paper proposes a deep learning-based framework for automatic weather forecasting. Our framework is a variant of the Convolutional Neural Network (CNN) model, which exploits the encoder and decoder to learn parameterizations from the given data and forecast weather. The proposed model can interpret spatial information associated with geopotential fields and automatically infers forecasting know-how with higher accuracy levels. A variable selection process is incorporated to determine geopotential height that impacts the weather conditions. We proposed an algorithm called Deep Weather Forecasting (DWF) to realize the proposed framework. Our empirical study has revealed that the proposed framework evaluates different deep learning models and compares their performance. Our deep learning models outperformed many existing regression models. U-

Net showed the highest performance with the least MAE, 0.2268, compared to all other models. In the future, we intend to improve our framework by proposing a hybrid model that uses linear and non-linear prediction models.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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