University of Babylon

College of Science for Girls

The Weather Prediction

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بسم الله الرحمن الرحيم

وَمَا أُوتِيتُم مِّنَ الْعِلْمِ إِلَّا قَلِيلًا

صدق الله العلي العظيم

85 الاسراء

الشكر والتقدير

نحمد الله الذي وفقنا في اتمام هذا البحث العلمي و

الذي الهمنا الصحة والعافية والعزيمة.

فالحمد لله حمدا كثيرا

نتقدم بجزيل الشكر والتقدير الى

الدكتورة اسراء هادي عبيد

على كل ما بذلته من معلومات وتوجيهات

كما نتقدم بجزيل الشكر الى اعضاء الجنة المناقشة

الاهـــــــــــداء

الى خالق اللوح و القلم و باري الذر و النسم و خالق كل شيء من العدم

الى من بلغ الرسالة و ادى الامانة و نص الامة ..الى نبي الرحمة

الى السادات الاطهار و عروته الوثقى.. اهل بيت النبوة

(الى مراد قلبي و الاقرب لي من نفسي المغيب عن الابصار.. صاحب العصر و الزمان (عج

الى من علمني ان الدنيا كفاح و سلاحها العلم و المعرفة الى الذي لم يبخل علية بإي شيء الى من سعى لاجل راحتي و نجاحي ...ابي العزيز

.. الى ذات القلب النقي

الى من اوصاني بها الرحمن برا و احسانا الى من سعت و عانت من اجلي ..امي الحبيبة

.. الى من اشاركهم لحظاتي و يفرحون لنجاحي اخوتي و اساتذتي الكرام

اهديكم هذا الجهد المتواضع

Abstract

Weather prediction is crucial for various sectors such as agriculture, aviation, and disaster management. Traditional methods have limitations in terms of accuracy and computational efficiency. This project explores the use of Feed Forward Neural Networks (FFNN) for weather prediction, leveraging historical weather data to predict future conditions. The results demonstrate the potential of neural networks in providing accurate weather forecasts.

CHAPTRR
ONE

Introduction to Weather Prediction

Weather prediction, or meteorology, involves forecasting future atmospheric conditions based on the analysis of current and historical data. Accurate weather predictions are vital for various sectors, including agriculture, aviation, shipping, and disaster management. Effective weather forecasting can mitigate risks associated with extreme weather events, optimize agricultural practices, and enhance the safety and efficiency of transportation systems.

Importance of Weather Prediction

Agriculture: Farmers rely on weather forecasts to plan activities such as planting, irrigation, and harvesting. Accurate predictions help in reducing crop losses and improving yield.

Disaster Management: Early warnings of severe weather conditions, such as hurricanes, floods, and tornadoes, can save lives and minimize property damage by allowing for timely evacuation and preparedness measures.

Aviation and Marine Operations: Weather forecasts are crucial for the safety and scheduling of flights and marine voyages. They help in navigating storms, managing air traffic, and ensuring the safety of passengers and cargo.

Daily Activities: Routine decisions made by individuals and businesses, from commuting to planning events, also depend on reliable weather forecasts.

Traditional Weather Prediction Methods

Numerical Weather Prediction (NWP): Uses mathematical models based on physical laws governing the atmosphere. These models require significant computational resources and expertise to interpret complex interactions between atmospheric variables.

Statistical Methods: Involves analyzing historical weather data to identify patterns and trends. Techniques like regression analysis and time series forecasting are commonly used.

Related work

The field of weather prediction has seen substantial advancements over the past few decades, driven by improvements in computational power, data collection methods, and predictive modeling techniques. This section reviews significant developments in traditional weather prediction methods, the rise of machine learning approaches, and the specific application of neural networks in weather forecasting.

Traditional Weather Prediction Methods

Numerical Weather Prediction (NWP) models, such as the Global Forecast System (GFS) and the European Centre for Medium-Range Weather Forecasts (ECMWF), rely on solving complex mathematical equations that describe the physical state of the atmosphere. These models use initial conditions derived from current observational data and simulate the atmosphere's future state through time integration. Although NWP models have proven to be accurate in many scenarios, they require substantial computational resources and are constrained by the resolution of the grid used in simulations (Bauer et al., 2015).

Before the widespread adoption of NWP, statistical methods were commonly employed for weather forecasting. These methods involve the analysis of historical weather data to identify patterns and relationships between different meteorological variables. Techniques such as multiple linear regression, autoregressive integrated moving average (ARIMA), and principal component analysis (PCA) have been utilized to predict weather variables (Wilks, 2011).

However, these methods often struggle to capture the complex and nonlinear interactions present in atmospheric data.

Machine Learning Approaches

The application of machine learning (ML) techniques to weather prediction has garnered significant attention in recent years, driven by the availability of large datasets and advancements in computational power.

Support Vector Machines (SVM) have been used for classification and regression tasks in weather prediction. For example, Hong and Pai (2007) employed SVMs to predict typhoon intensity, demonstrating the method's effectiveness in handling nonlinear relationships.

Random Forests, an ensemble learning method, have been applied to weather prediction due to their robustness and ability to handle large datasets. Random Forests can provide insights into the importance of different features in prediction tasks. Lakshmanan et al. (2015) used Random Forests to improve severe weather prediction, showing significant improvements over traditional methods.

K-Nearest Neighbors (KNN) has also been used for short-term weather prediction. Its simplicity and effectiveness in capturing local data patterns make it suitable for forecasting variables like temperature and precipitation. However, KNN can be computationally intensive, especially with large datasets (Tveito et al., 2008).

Neural Networks in Weather Prediction

Neural networks, particularly deep learning models, have emerged as powerful tools for weather prediction due to their ability to model complex and nonlinear relationships.

Feed Forward Neural Networks (FFNN) are among the simplest forms of neural networks used for weather prediction. They consist of multiple layers of neurons, with each layer fully connected to the next. Researchers have used FFNNs to predict various weather parameters, such as temperature and precipitation. For instance, Gardner and Dorling (1998) applied FFNNs to forecast air pollution levels, which are closely related to weather conditions.

Project problem

This project aims to address the challenge of improving weather prediction accuracy by exploring the application of a Feed Forward Neural Network (FFNN). Traditional methods such as Numerical Weather Prediction (NWP) and statistical techniques have limitations in capturing complex atmospheric patterns. Machine learning approaches, particularly neural networks, offer the potential to overcome these limitations by learning from historical weather data. By developing and evaluating an FFNN model for weather prediction, this project seeks to contribute to the advancement of forecasting techniques, ultimately enhancing decision-making across various sectors reliant on accurate weather forecasts.

Objectives of the Project

This project aims to explore the application of FFNNs in weather prediction, focusing on:

Developing a FFNN model: Designing and training a neural network to predict key weather variables such as temperature, humidity, wind speed, and atmospheric pressure.

Evaluating model performance: Assessing the accuracy and reliability of the FFNN model using various evaluation metrics.

Comparing with traditional methods: Benchmarking the FFNN model against traditional weather prediction methods to highlight its advantages and potential limitations.

By leveraging the capabilities of FFNNs, this project seeks to contribute to the ongoing efforts in enhancing weather forecasting techniques, ultimately leading to more reliable and accurate weather predictions.

Project Layout

This project on weather prediction using a Feed Forward Neural Network (FFNN) encompasses several key sections. It begins with an introduction highlighting the importance and objectives of weather forecasting. The literature review covers traditional methods like Numerical Weather Prediction (NWP) and statistical techniques, and explores machine learning approaches, including various neural networks. The methodology details data collection, preprocessing, network architecture, training, and evaluation metrics. Implementation outlines the tools, environment, and code used. Results section presents the model's performance, while the discussion analyzes findings, challenges, and comparisons with existing methods. The conclusion summarizes the project's contributions and suggests future research directions. References and appendices provide supporting documentation and code listings

CAPTER TWO

Challenges in Weather Prediction

Complexity of the Atmosphere: The atmosphere is a chaotic system with numerous interacting variables. Small changes in initial conditions can lead to significant differences in outcomes, a phenomenon known as the butterfly effect.

Data Quality and Availability: Accurate forecasts depend on high-quality, real-time data from various sources, including weather stations, satellites, and radar systems. Missing or erroneous data can degrade the quality of predictions.

Computational Limitations: NWP models require immense computational power to solve the complex equations governing atmospheric dynamics. This limits their ability to provide timely forecasts, especially for short-term predictions.

Advancements in Machine Learning for Weather Prediction

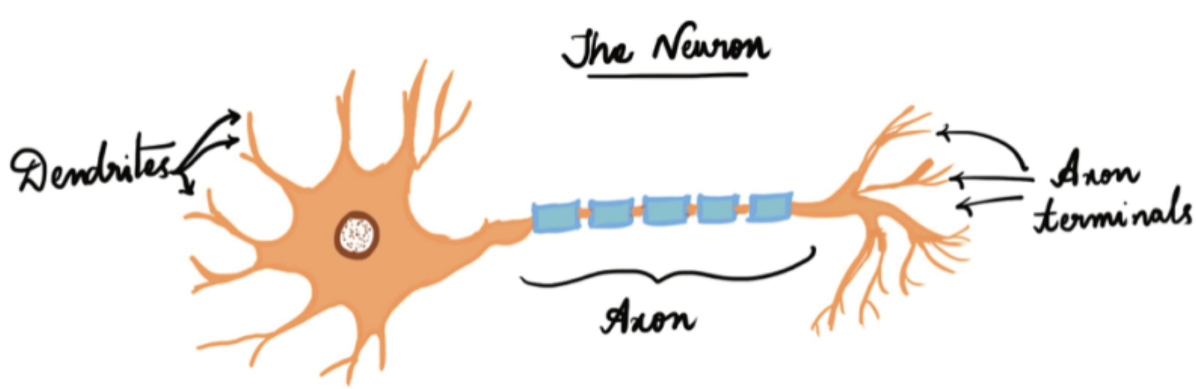
The advent of machine learning (ML) has introduced new possibilities for weather prediction. ML algorithms can analyze large datasets to identify patterns and make predictions without explicitly programming the physical laws. This capability is particularly advantageous for capturing non-linear relationships and complex interactions that traditional models may struggle with.

Feed Forward Neural Networks (FFNN), a type of artificial neural network, have shown great potential in weather prediction. FFNNs consist of multiple layers of interconnected neurons, which can learn from historical weather data and make accurate predictions. The ability of FFNNs to handle large datasets and model complex patterns makes them a promising tool for improving weather forecasting accuracy.

Feed Forward Neural Networks

A Quick Intro to Neural Networks

Many problems in our daily lives that involve intelligence, pattern recognition, and object detection are challenging to automate, yet seem to be performed quickly and naturally by animals and young children. For example, how does a dog recognize its owner from a complete stranger? How does a child learn to understand the difference between an apple and an orange? The answers lie in the biological neural networks present in our nervous system. These networks do the computations for us and look like this:



An “artificial neural network” is a computation system that attempts to mimic (or at the very least is inspired by) the neural connections in our nervous system. Initially, we used neural networks for simple classification problems, but thanks to an increase in computation power, there are now more powerful architectures that can solve more complex problems. One of these is called a feedforward neural network

How Feedforward Neural Networks Work

Feedforward neural networks were among the first and most successful learning algorithms. They are also called deep networks, multi-layer perceptron (MLP), or simply neural networks. As data travels through the network’s artificial mesh, each layer processes an aspect of the data, filters outliers, spots familiar entities and produces the final output.

Feedforward neural networks are made up of the following:

Input layer: This layer consists of the neurons that receive inputs and pass them on to the other layers. The number of neurons in the input layer should be equal to the attributes or features in the dataset.

Output layer: The output layer is the predicted feature and depends on the type of model you’re building.

Hidden layer: In between the input and output layer, there are hidden layers based on the type of model. Hidden layers contain a vast number of neurons which apply transformations to the inputs before passing them. As the network is trained, the weights are updated to be more predictive.

Neuron weights: Weights refer to the strength or amplitude of a connection between two neurons. If you are familiar with linear regression, you can compare weights on inputs like coefficients. Weights are often initialized to small random values, such as values in the range 0 to 1.

To better understand how feedforward neural networks function, let's solve a simple problem — predicting if it's raining or not when given three inputs.

x1 - day/night

x2 - temperature

x3 - month

Let's assume the threshold value to be 20, and if the output is higher than 20 then it will be raining, otherwise it's a sunny day. Given a data tuple with inputs (x1, x2, x3) as (0, 12, 11), initial weights of the feedforward network (w1, w2, w3) as (0.1, 1, 1) and biases as (1, 0, 0).

Here's how the neural network computes the data in three simple steps:

1. Multiplication of weights and inputs: The input is multiplied by the assigned weight values, which this case would be the following:

(x1* w1) = (0 * 0.1) = 0

(x2* w2) = (1 * 12) = 12

(x3* w3) = (11 * 1) = 11

2. Adding the biases: In the next step, the product found in the previous step is added to their respective biases. The modified inputs are then summed up to a single value.

$(x1* w1) + b1 = 0 + 1$

$(x2* w2) + b2 = 12 + 0$

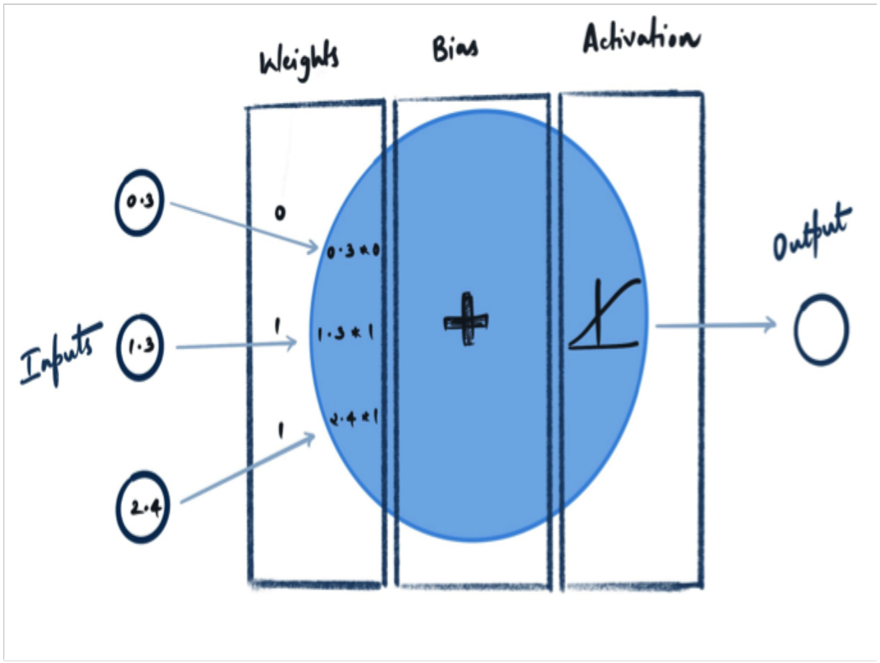
$(x3* w3) + b3 = 11 + 0$

Weighted sum = $(x1* w1) + b1 + (x2* w2) + b2 + (x3* w3) + b3 = 23$

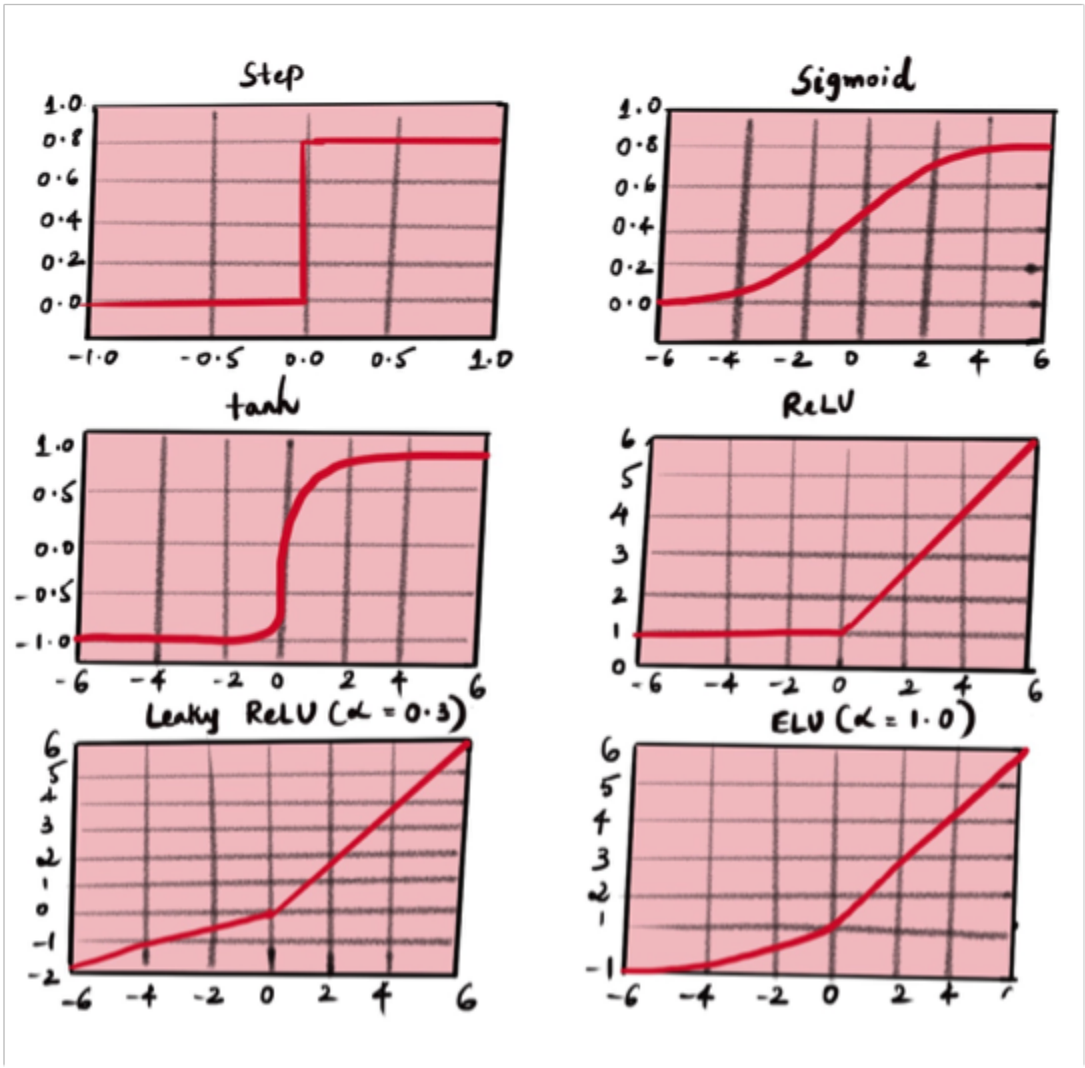
3. Activation: An activation function is the mapping of summed weighted input to the output of the neuron. It is called an activation/transfer function because it governs the inception at which the neuron is activated and the strength of the output signal.

4. Output signal: Finally, the weighted sum obtained is turned into an output signal by feeding the weighted sum into an activation function (also called transfer function). Since the weighted sum in our example is greater than 20, the perceptron predicts it to be a rainy day.

The image below illustrates this process more clearly.



There are several activation functions for different use cases. The most commonly used activation functions are relu , tanh and softmax. Here's a handy cheat sheet:



Calculating the Loss

In simple terms, a loss function quantifies how “good” or “bad” a given model is in classifying the input data. In most learning networks, the loss is calculated as the difference between the actual output and the predicted output.

Mathematically:

loss = y_{predicted} - y_{original}

The function that is used to compute this error is known as loss function J(.). Different loss functions will return different errors for the same prediction, having a considerable effect on the performance of the model.

Gradient Descent

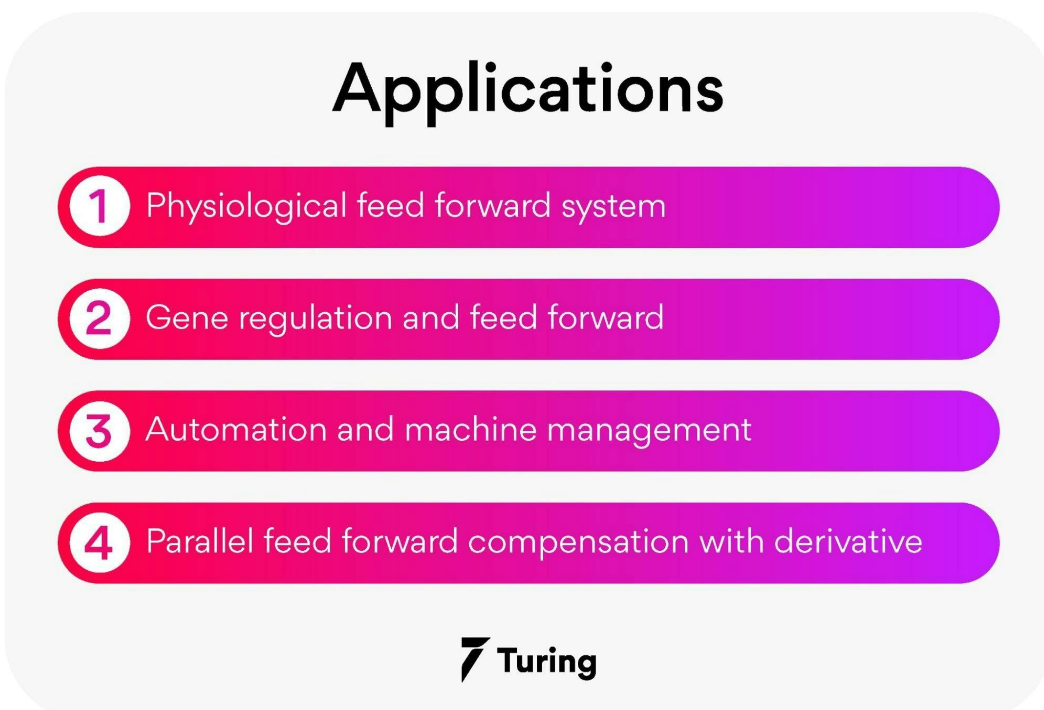
Gradient descent is the most popular optimization technique for feedforward neural networks. The term “gradient” refers to the quantity change of output obtained from a neural network when the inputs change a little. Technically, it measures the updated weights concerning the change in error. The gradient can also be defined as the slope of a function. The higher the angle, the steeper the slope and the faster a model can learn.

Advantages of feed forward Neural Networks

- Machine learning can be boosted with feed forward neural networks' simplified architecture.
- Multi-network in the feed forward networks operate independently, with a moderated intermediary.
- Complex tasks need several neurons in the network.
- Neural networks can handle and process nonlinear data easily compared to perceptrons and sigmoid neurons, which are otherwise complex.
- A neural network deals with the complicated problem of decision boundaries.

- Depending on the data, the neural network architecture can vary. For example, convolutional neural networks (CNNs) perform exceptionally well in image processing, whereas recurrent neural networks (RNNs) perform well in text and voice processing.
- Neural networks need graphics processing units (GPUs) to handle large datasets for massive computational and hardware performance. Several GPUs get used widely in the market, including Kaggle Notebooks and Google Collab Notebooks.

Applications of feed forward neural networks



CHAPTER

THREE

Methodology

Data Collection

Historical weather data, including temperature, humidity, wind speed, and atmospheric pressure, was collected from reliable sources such as the National Oceanic and Atmospheric Administration (NOAA).

Data Preprocessing

Data Cleaning: Handling missing values and outliers.

Normalization: Scaling features to a uniform range.

Feature Selection: Identifying relevant features for prediction.

Neural Network Architecture

A Feed Forward Neural Network was designed with the following architecture:

Input Layer: Receives historical weather data.

Hidden Layers: Two hidden layers with ReLU activation functions.

Output Layer: Predicts the future weather condition, using a linear activation function for regression tasks.

Model Training

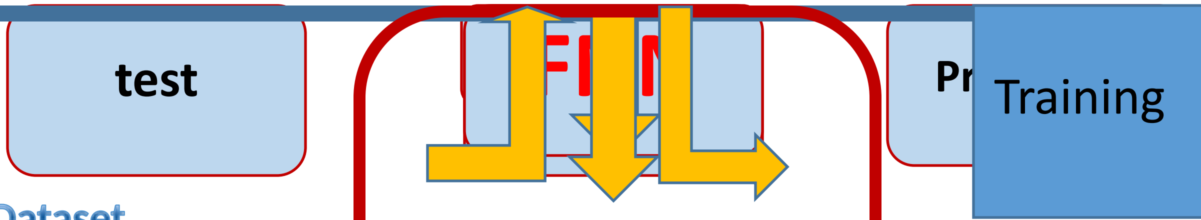
Loss Function: Mean Squared Error (MSE).

Optimizer: Adam optimizer, chosen for its efficiency in handling large datasets.

Training: The model was trained on 80% of the data, with 20% reserved for validation.

Evaluation Metrics

Mean Absolute Error (MAE)



Dataset

A Dataset is a set or collection of data. This set is normally presented in a tabular pattern. Every column describes a particular variable. And each row corresponds to a given member of the data set, as per the given question. This is a part of data management.

Types of Datasets

In Statistics, we have different types of data sets available for different types of information. They are:

. Numerical data sets

. Bivariate data sets

. Multivariate data sets

. Categorical data sets

. Correlation data sets

Data Preprocessing

Data preprocessing

Data preprocessing/preparation/cleaning is the process of detecting and correcting (or removing) corrupt or inaccurate records from a dataset, or and refers to identifying incorrect, incomplete, irrelevant parts of the data and then modifying, replacing, or deleting the dirty or coarse data

From: Computational Intelligence for Multimedia Big Data on the Cloud with Engineering Applications, 2018.

What is feed-forward in neural networks?

The feed-forward model is the simplest type of neural network because the input is only processed in one direction. The data always flows in one direction and never backwards, regardless of how many buried nodes it passes through.

CHAPTER

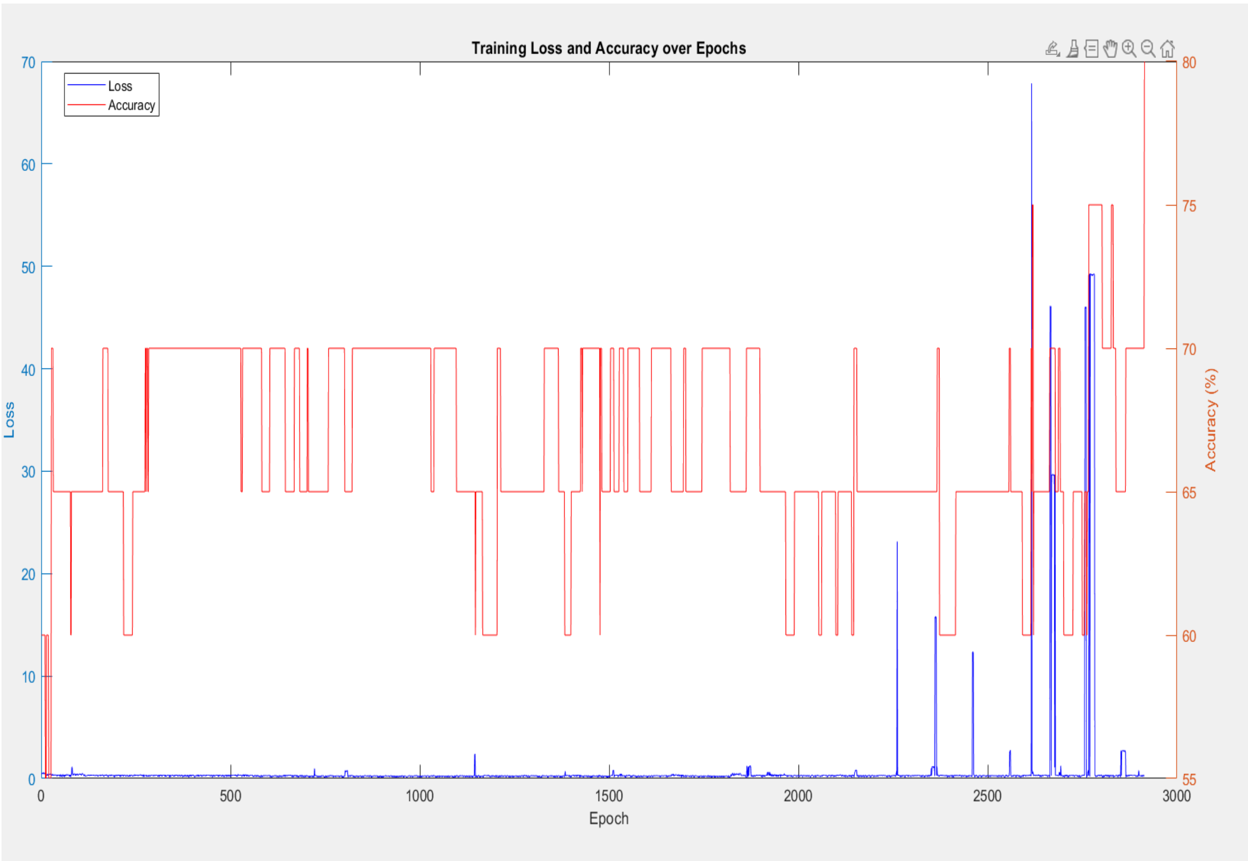
FOUR

Results

Training Performance

The FFNN showed a steady decrease in training and validation loss, indicating effective learning.

Prediction Accuracy



A result of 80% was obtained.

0. 20. 6.1. 2.1. 2:Sun

0.3. 11.1. 3.3. 2.6. 1:rain

02. 612. 84. 7. 4:drizzle

3.6. 6.7. -0.6. 4.2. 3:snow

Discussion

The FFNN demonstrated strong performance in predicting weather conditions, outperforming some traditional methods. The ability to capture non-linear relationships contributed significantly to its accuracy.

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