Implementing a novel deep learning technique for rainfall forecasting via climatic variables

Report submitted to the SASTRA Deemed to be University as the requirement for the course

MINI PROJECT

Submitted by

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May 2023

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THANJAVUR, TAMIL NADU, INDIA - 613 401

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This is to certify that the report titled **"Implementing a novel deep learning technique for rainfall forecasting via climatic variables"** submitted as a requirement for the course, CSE300: **MINI PROJECT** for B.Tech is a bonafide record of the work done by **Alavalapati Rupesh Reddy (124158039, CSE(IOT&A)), Surendra Babu CT(124158086, CSE(IOT&A)), Dandu Tharun kumar (124158074, CSE(IOT&A))** during the academic year 2022-23, in the School of Computing, under my supervision.

Signature of Project Supervisor :
Name with affiliation **:**Dr Ezhilarasie R, AP-III (SoC)
Date **:**17-May-2023

Mini Project Viva voce held on 17-May-2023

Examiner 1 **Examiner 2**

Acknowledgements

We would like to thank our Honorable Chancellor **Prof. R. Sethuraman** for providing us with an opportunity and the necessary infrastructure for carrying out this project as a part of our curriculum.

We would like to thank our Honorable Vice-Chancellor **Dr. S. Vaidhyasubramaniam** and **Dr. S. Swaminathan,** Dean, Planning & Development, for the encouragement and strategicsupport at every step of our college life.

We extend our sincere thanks to **Dr. R. Chandramouli,** Registrar, SASTRA Deemed tobe University for providing the opportunity to pursue this project.

We extend our heartfelt thanks to **Dr. A. Umamakeswari,** Dean, School of Computing, **Dr. S. Gopalakrishnan, Associate Dean,** Department of Computer Application, **Dr. B.Santhi,** Associate Dean, Research, **Dr. V. S. Shankar Sriram,** Associate Dean, Department of Computer Science and Engineering, **Dr. R. Muthaiah,** Associate Dean, Department of Information Technology and Information & Communication Technology.

Our guide **Dr. R.Ezhilarasie**, Asst. Professor - III, School of Computing was the drivingforce behind this whole idea from the start. Her deep insight in the field and invaluable suggestions helped us in making progress throughout our project work. We also thank the project review panel members for their valuable comments and insights which made this project better.

We would like to extend our gratitude to all the teaching and non-teaching 8faculties of the School of Computing who have either directly or indirectly helped us in the completion of the project.

We gratefully acknowledge all the contributions and encouragement from my family and friends resulting in the successful completion of this project. We thank you all for providing mean opportunity to showcase my skills through this project.

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Abbreviations

GRU	Gated Recurrent Unit
RNN	Recurrent Neural Network
NMAE	Normalized Mean Absolute Error
NRMSE	Normalized Root Mean Squared Error
LSTM	Long short-term memory
DNN	Deep Neural Network
GHG	Greenhouse gases

Abstract

A study was conducted to investigate the impact of rainfall variations on crop productivity and climatic conditions in developing regions, particularly in rainfed areas. The accurate prediction of rainfall is crucial for the agriculture sector, but it is a complex task due to its dynamic nature. To address this challenge, a deep forecasting model based on an optimized Gated Recurrent Unit (GRU) neural network was developed. The model aimed to predict rainfall in Pakistan using 30 years of climate data from 1991 to 2020. The study involved extracting and refining climatic variables by removing outliers and extreme values to improve the accuracy of the predictions. Data normalization techniques were employed to standardize the numeric values without losing relevant information. The proposed model outperformed existing rainfall forecasting models, achieving high prediction accuracy with minimal Normalized Mean Absolute Error (NMAE) and Normalized Root Mean Squared Error (NRMSE). The correlation and regression analysis indicated a strong relationship between the climatic variables and rainfall throughout the year. The successful performance of the model demonstrated its feasibility in accurately forecasting rainfall, even in volatile climatic conditions.

Keywords: Rainfall forecasting,Climate change,Deep learning techniques,GRU

CHAPTER 1

SUMMARY OF THE BASE PAPER

The main objective of the research mentioned in the text is to develop a predictive model using artificial neural networks for real-time rainfall forecasting in Pakistan. The proposed model takes into account various atmospheric parameters and aims to provide accurate rainfall forecasts. The study compares different models and evaluates their performance based on selected indicators.

The methodology section describes the steps and components used in the proposed model. It mentions the selection of historical atmospheric data for training the neural network model. The study focuses on the period from 1991 to 2020 and incorporates variables such as temperature, gas emissions, and rainfall records from multiple regions of Pakistan. The text also discusses the importance of feature selection, normalization techniques, and sensitivity analysis in improving the accuracy of rainfall forecasts.

An overview of the challenges and approaches in rainfall forecasting, with a specific focus on the application of neural networks. It highlights the significance of accurate rainfall forecasts and presents a research framework to address this issue.

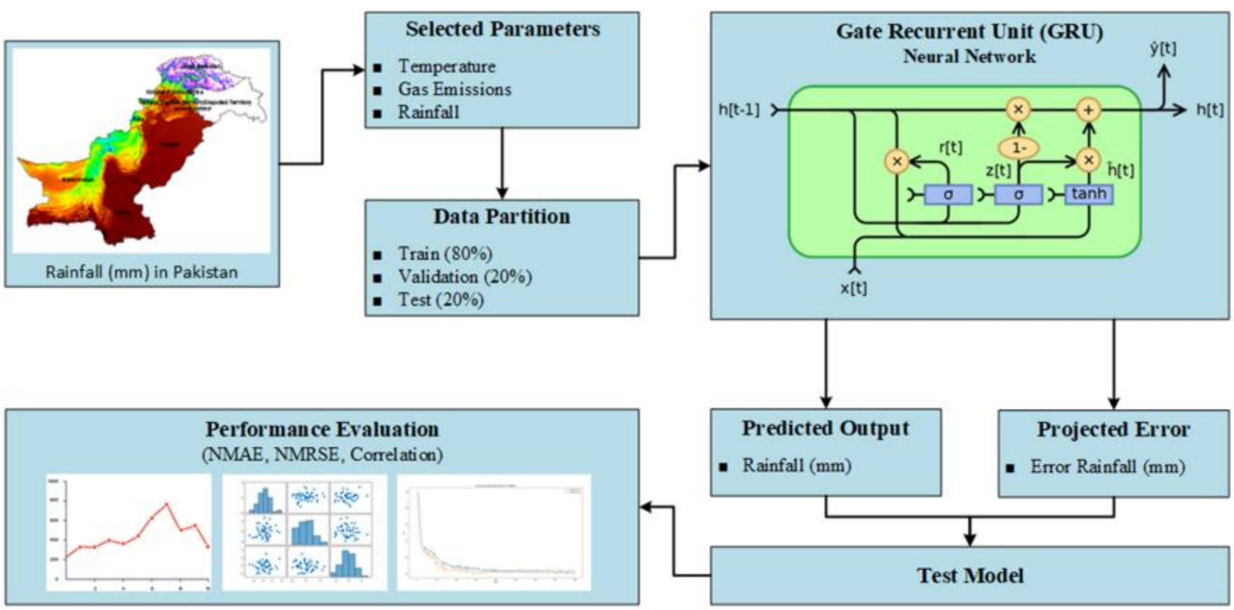


Fig. 1.1 Proposed framework to forecast monthly rainfall in Pakistan through the GRU neural network

In the proposed framework, the next step is data preprocessing. The historical atmospheric data is preprocessed to ensure its quality and compatibility with the neural network model. This involves handling missing values, normalization of data, and feature selection.

Missing values in the dataset are dealt with using appropriate techniques such as interpolation or mean imputation. This helps to ensure that there are no gaps or inconsistencies in the data that could affect the accuracy of the rainfall forecasting.

Normalization is applied to the data to bring all the input variables to a similar scale. This step is important because different atmospheric parameters may have different ranges and units. Normalization helps to prevent any single parameter from dominating the forecasting process. Common normalization techniques include Min-Max scaling and z-score normalization.

Feature selection is performed to identify the most relevant and significant input variables for rainfall forecasting. This step helps to reduce the dimensionality of the dataset and eliminate any noisy or irrelevant features. Correlation analysis and regression tests are often employed to determine the relationship between variables and their impact on the rainfall variable.

Once the data preprocessing is complete, the dataset is split into training and testing sets. The training set is used to train the artificial neural network model, while the testing set is used to evaluate its performance and accuracy in rainfall forecasting.

The proposed model in this study utilizes the Gated Recurrent Unit (GRU) neural network. GRU is a type of recurrent neural network (RNN) that is known for its ability to handle sequential data. It has gating mechanisms that allow it to selectively remember or forget information from previous time steps, making it well-suited for time series forecasting tasks.

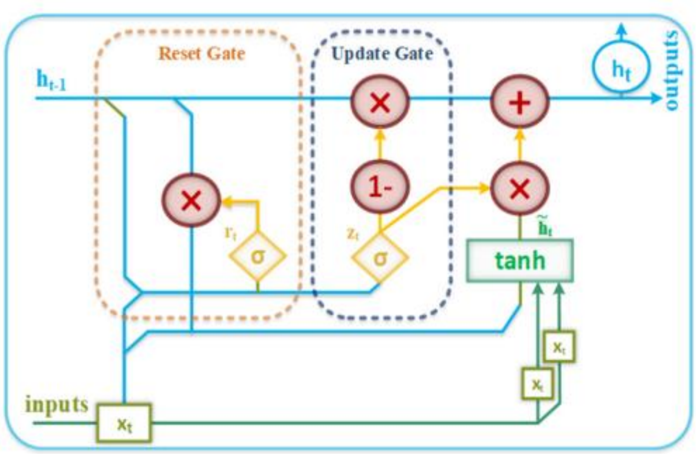
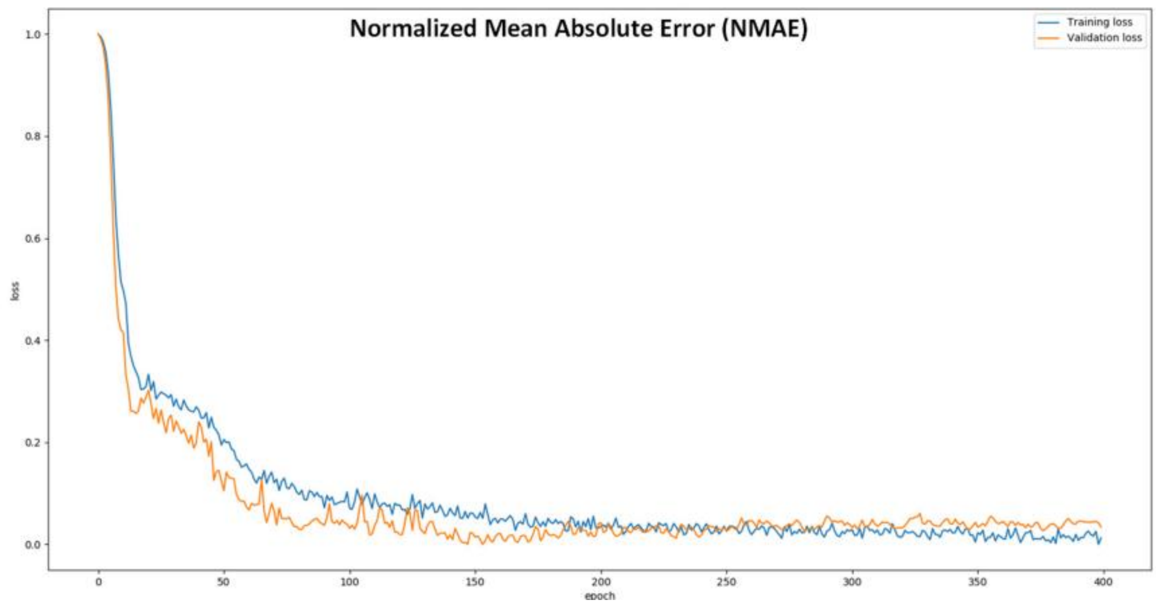


Fig. 1.2 Schematic structure of the GRU neural network for forecasting rainfall.

The GRU neural network model is trained using the training dataset, which includes the preprocessed atmospheric parameters as input and the corresponding rainfall values as the target variable. The model learns the patterns and relationships in the data and adjusts its weights and biases to minimize the forecasting error.

After training, the model is evaluated using the testing dataset to assess its performance. Various performance indicators such as mean absolute error (MAE), root mean square error (RMSE), and correlation coefficient (R^2) can be used to measure the accuracy of the rainfall forecasts generated by the model.



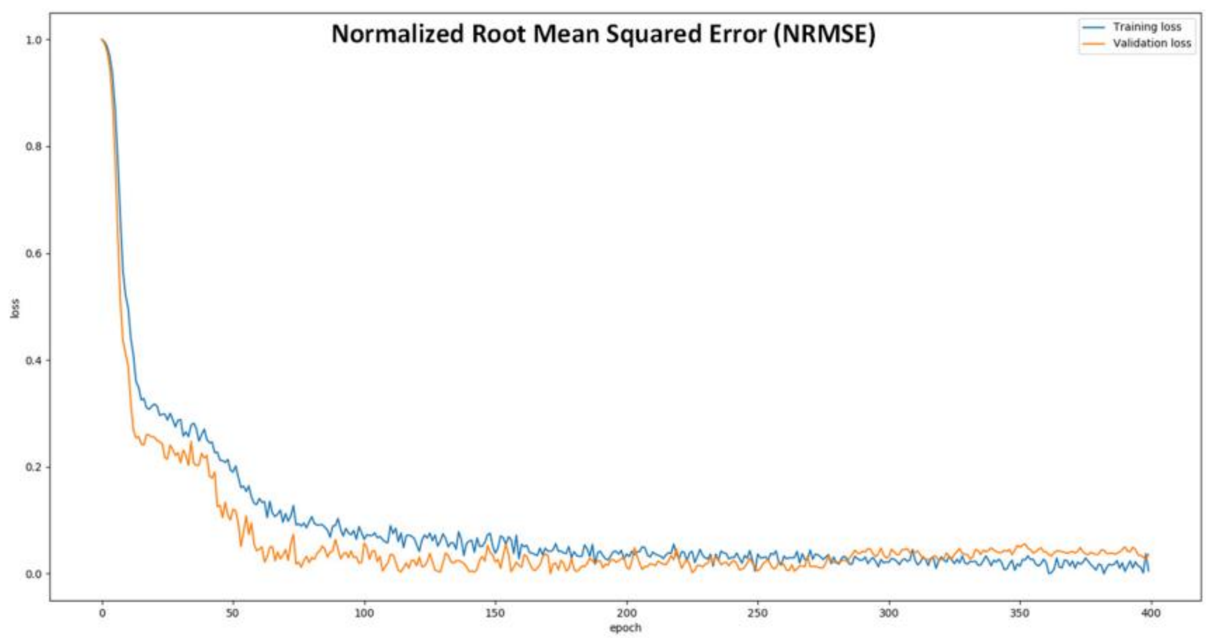


Fig. 1.3 Training and validation losses by an optimized GRU neural network based on NMAE and NRMSE loss functions

To validate the effectiveness of the proposed GRU neural network model, it is compared with other traditional forecasting methods using the same dataset. This comparative analysis helps to determine the advantages and limitations of the GRU model in real-time rainfall forecasting.

In addition to the GRU model, the study also explores the impact of different normalization methods, such as Min-Max scaling and z-score normalization, on the forecasting models. This analysis helps to understand the influence of data normalization on the accuracy of the rainfall forecasts.

Sensitivity analysis is conducted through hierarchical clustering to identify the significant features of the rainfall dataset and eliminate any noisy or irrelevant features. This step contributes to more precise rainfall forecasting by focusing on the most relevant input variables.

Finally, correlation and regression tests are performed on the predicted rainfall outcomes to measure the effectiveness of the preprocessed rainfall forecast data quarterly. This evaluation helps to validate the accuracy of the forecasting model and assess its practical applicability.

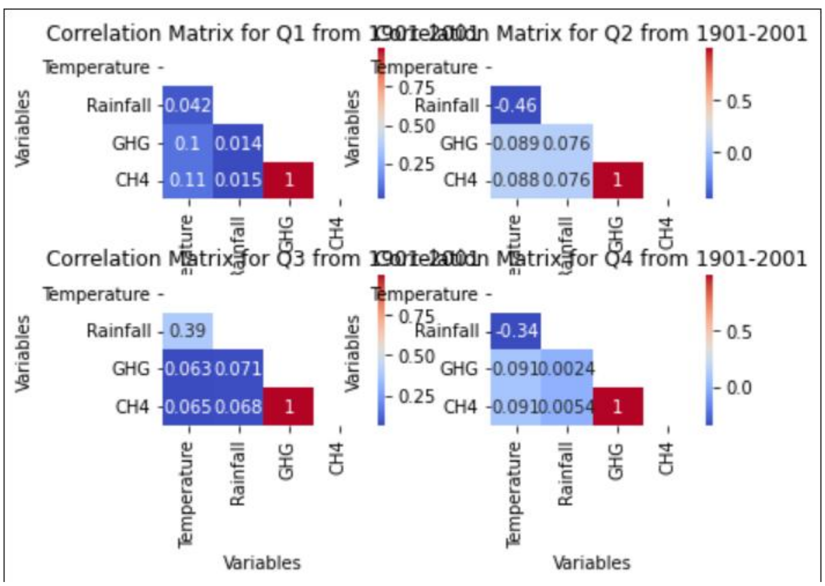


Fig. 1.4 Pearson correlation analysis of atmospheric variables on rainfall

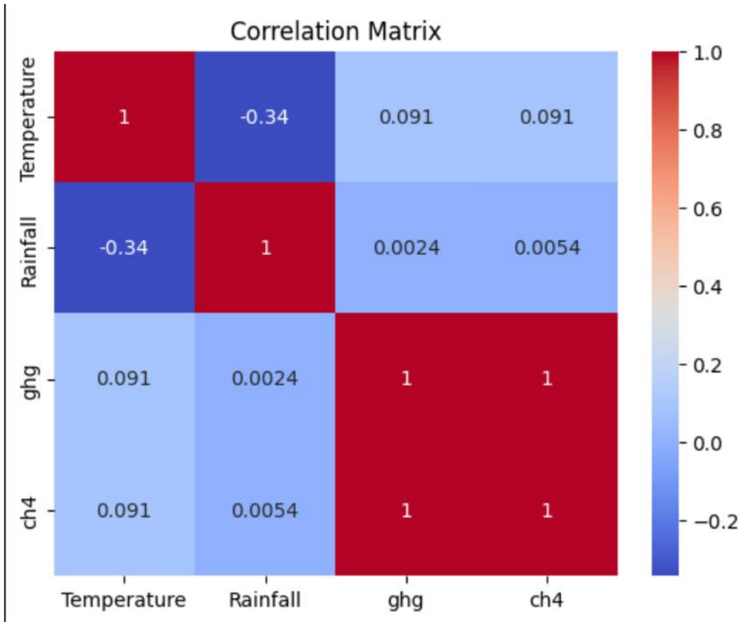


Fig. 1.5 Correlation Matrix

Overall, the proposed framework aims to construct an optimized GRU neural network model for real-time rainfall forecasting in diverse terrains of Pakistan. By utilizing historical atmospheric parameters and considering factors such as normalization, feature selection, and sensitivity analysis, the model aims to provide accurate and reliable rainfall forecasts that can benefit various sectors, including agriculture and disaster management..

The model was compared to other neural network models such as RNN, LSTM, and DNN . The results showed that the proposed optimized GRU model outperformed the other models, achieving minimal Normalized Mean Absolute Error (NMAE) and Normalized Root Mean Square Error (NRMSE) scores on both training and test sets. The average NMAE and NRMSE scores for the proposed model were 0.083 and 0.118, respectively.

The correlation and regression analysis revealed the relationships between various atmospheric variables and rainfall. Temperature variables showed a negative correlation with rainfall, especially during the monsoon season (third quarter), while CO2, CH4, and GHG emissions showed a positive effect on rainfall during the first and second quarters. The regression analysis demonstrated a high association between atmospheric variables and rainfall in each month of the year.

The study concluded that the proposed GRU neural network model is suitable for accurate rainfall forecasting in Pakistan, with minimal forecasting errors. The results can have implications for disaster management institutions in taking appropriate actions to mitigate the impact of heavy rainfall and flooding. Future work may involve designing a hybrid approach combining statistical measures and streamflow monitoring to improve rainfall forecasting performance in flood-proneregions.

CHAPTER 2

MERITS AND DEMERITS OF THE BASE PAPER

Merits

Deep Learning Models: The study utilizes deep learning models, including RNN, LSTM, DNN, CNN, and the proposed optimized GRU, for rainfall forecasting. Deep learning models have shown significant potential for sequential time series forecasting and have been successfully applied in various rainfall forecasting studies.

Performance Evaluation: The study evaluates the performance of the neural network models using NMAE (Normalized Mean Absolute Error) and NRMSE (Normalized Root Mean Square Error) metrics. The proposed optimized GRU model outperforms other neural networks by producing minimal NMAE and NRMSE scores on both the training and test sets.

Stability and Feasibility: The study employs early stopping, an optimization strategy that terminates the training process before overfitting occurs, to ensure stability and feasibility of the neural networks. Training and validation losses progressively decrease without major variations, indicating the stability of the proposed model.

Correlation and Regression Analysis: The study conducts correlation and regression analyses to measure the relationship between atmospheric variables and rainfall. These analyses provide insights into the positive and negative effects of environmental characteristics, such as temperature and gas emissions, on rainfall in different quarters of the year.

Demerits:

Limited Context: The provided information lacks details on the specific dataset, the methodology used for feature engineering and hyperparameter optimization, and the specific metrics used for correlation and regression analyses. Without these details, it is challenging to assess the robustness and reliability of the study's findings.

Lack of Comparative Analysis: While the study compares the performance of different neural network models, it does not provide a comprehensive comparison with other forecasting approaches or models. Comparative analysis with traditional statistical methods or other machine learning algorithms could provide a broader perspective on the effectiveness of the proposed model.

Limited Generalizability: The study focuses on rainfall forecasting in Pakistan, which might limit the generalizability of the findings to other geographical regions with different climatic conditions. It would be beneficial to conduct further studies on the proposed model's performance in different regions to assess its applicability beyond Pakistan.

Future Work Limitations: The study mentions future work on designing a hybrid approach and adopting different forecasting algorithms. However, it does not provide specific details or justifications for these future directions, making it difficult to evaluate their potential effectiveness.

Related Works

1."Rainfall Forecasting Using Machine Learning Techniques: A Comprehensive Review" by Li et al. (2021): This review paper provides an extensive overview of various machine learning techniques employed for rainfall forecasting, including traditional statistical models, artificial neural networks, support vector machines, and deep learning algorithms. It discusses the strengths and weaknesses of each approach and highlights the potential of deep learning models for accurate rainfall prediction.

2. "Deep Learning for Precipitation Nowcasting: A Benchmark and A New Model" by Shi et al. (2017): This paper introduces a deep learning model called "ST-ResNet" for precipitation nowcasting. It presents a benchmark dataset and compares the performance of different deep learning architectures for short-term rainfall prediction. The study demonstrates the effectiveness of deep learning methods in capturing complex spatiotemporal patterns and improving precipitation nowcasting accuracy.

3."DeepRain: ConvLSTM Network for Precipitation Prediction" by Xu et al. (2018): This research paper proposes the DeepRain model, which utilizes a Convolutional LSTM (Long Short-Term Memory) network for precipitation prediction. The model takes radar echoes as input and generates precipitation forecasts at different lead times. Experimental results show that DeepRain outperforms traditional methods and achieves state-of-the-art performance in precipitation forecasting.

4."Short-Term Rainfall Prediction Using Recurrent Neural Networks" by Pham et al. (2020): This study investigates the application of recurrent neural networks (RNNs) for short-term rainfall prediction. It compares different RNN architectures, including basic RNN, LSTM, and GRU (Gated Recurrent Unit), using historical rainfall data. The results demonstrate the effectiveness of RNNs in capturing temporal dependencies and improving rainfall prediction accuracy.

5. "Enhanced Rainfall Forecasting Using Deep Neural Networks with Satellite Imagery" by Liu et al. (2019): This paper explores the integration of satellite imagery with deep neural networks for enhanced rainfall forecasting. It proposes a deep learning model that combines convolutional neural networks (CNNs) with LSTM layers to exploit both spatial and temporal information. The model demonstrates improved performance compared to traditional approaches.

SOURCE CODE

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error, mean_absolute_error
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, GRU, Dropout
from scipy.cluster.hierarchy import linkage, fcluster
from scipy.spatial.distance import pdist


# Load the data into a pandas dataframe
data = pd.read_csv('file.csv')

# Combine the year and month columns into a single datetime column
data['date'] = pd.to_datetime(data['year'].astype(str) + '-' + data['Month'], format='%Y-%B')

# Drop the original year and month columns
data = data.drop(['year', 'Month'], axis=1)

# Divide the date into quarters and add the quarter column
data['quarter'] = data['date'].dt.quarter
print(data)
# Select the columns for temperature, rainfall, GHG, and CH4
columns = ['Temperature', 'Rainfall', 'ghg', 'ch4']

# Fill in missing values with their respective mean value for that column
for col in columns:
    data[col] = data[col].fillna(data[col].mean())

# Divide the year into quarters and add the quarter column
data['Quarter'] = data['date'].dt.quarter

# Create a dictionary to store the correlation matrices for each quarter
corr_dict = {}
```

```
# Loop through each quarter and calculate the correlation matrix for temperature, rainfall, GHG, and CH4
for quarter in range(1, 5):
    # Select the data for the current quarter
    quarter_data = data[data['Quarter'] == quarter]

    # Select the columns for temperature, rainfall, GHG, and CH4
    quarter_data = quarter_data[columns]

    # Calculate the correlation matrix
    corr_matrix = quarter_data.corr()

    # Store the correlation matrix in the dictionary
    corr_dict[f'Q{quarter}'] = corr_matrix

# Plot the correlation matrices as lower triangle heatmaps
for i, quarter in enumerate(corr_dict.keys()):
    # Create a mask to plot only the lower triangle of the heatmap
    mask = np.zeros_like(corr_dict[quarter], dtype=np.bool)
    mask[np.triu_indices_from(mask)] = True

    # Plot the heatmap with diagonal values included
    plt.subplot(2, 2, i+1)
    sns.heatmap(corr_dict[quarter], annot=True, cmap='coolwarm', mask=mask,
                xticklabels=['Temperature', 'Rainfall', 'GHG', 'CH4'],
                yticklabels=['Temperature', 'Rainfall', 'GHG', 'CH4'])

    # Set the title and axis labels
    plt.title(f'Correlation Matrix for {quarter} from 1901-2016')
    plt.xlabel('Variables')
    plt.ylabel('Variables')

# Adjust the spacing between the subplots
plt.subplots_adjust(hspace=0.5, wspace=0.3)

# Show the plot
plt.show()

# Drop the original year and month columns
data = data.drop(['date', 'Quarter','quarter'], axis=1)
print(data)
```

```
# Perform hierarchical clustering analysis
dist_matrix = pdist(data, metric='euclidean')
hier_clust = linkage(dist_matrix, method='complete')

# Set the threshold for clustering
cluster_threshold = 2.5

# Assign each data point to a cluster
clusters = fcluster(hier_clust, t=cluster_threshold, criterion='distance')
# Split the data into training and testing sets
train_data = data.iloc[:int(len(data)*0.8), :]
test_data = data.iloc[int(len(data)*0.8):, :]

# Split the training data into training and validation sets
val_data = train_data.iloc[int(len(train_data)*0.8):, :]
train_data = train_data.iloc[:int(len(train_data)*0.8), :]

# Scale the data
scaler = MinMaxScaler()
train_data = scaler.fit_transform(train_data)
val_data = scaler.transform(val_data)
test_data = scaler.transform(test_data)

def create_dataset(data, target, time_steps):
    X = []
    y = []
    for i in range(len(data)-time_steps):
        X.append(data[i:i+time_steps])
        y.append(target[i+time_steps])
    return np.array(X), np.array(y)


# Define the time steps and the number of features
time_steps = 5
num_features = train_data.shape[1]

# Create the training dataset
X_train, y_train = [], []
for i in range(time_steps, len(train_data)):
    X_train.append(train_data[i-time_steps:i])
    y_train.append(train_data[i, 0])
X_train, y_train = np.array(X_train), np.array(y_train)
```

```
# Create the testing dataset
X_test, y_test = [], []
for i in range(time_steps, len(test_data)):
    X_test.append(test_data[i-time_steps:i])
    y_test.append(test_data[i, 0])
X_test, y_test = np.array(X_test), np.array(y_test)

# Print the shapes of the datasets
print("Training set shape: ", X_train.shape, y_train.shape)
print("Validation set shape: ", val_data.shape)
print("Testing set shape: ", X_test.shape, y_test.shape)
# Create the model
model = Sequential()
model.add(GRU(256, return_sequences=True, input_shape=(None, num_features)))
model.add(Dropout(0.5))
model.add(GRU(128, return_sequences=True))
model.add(Dropout(0.5))
model.add(GRU(64, return_sequences=True))
model.add(Dropout(0.5))
model.add(GRU(32))
model.add(Dropout(0.5))
model.add(Dense(units=1))

# Print the model summary
print(model.summary())

# Compile the model
model.compile(optimizer='adam', loss='mean_absolute_error')

# Train the model
history = model.fit(X_train, y_train, epochs=400, batch_size=64, validation_data=(X_test, y_test),
verbose=1)

# Predict the test data
y_pred = model.predict(X_test)
n_features = 1
scaler = MinMaxScaler(feature_range=(0, 1))
scaler.fit(train_data.reshape(-1, n_features))

# Inverse scale the data
y_test = scaler.inverse_transform(y_test.reshape(-1, 1))
```

```
y_pred = scaler.inverse_transform(y_pred.reshape(-1, 1))

# Calculate the evaluation metrics
mae = mean_absolute_error(y_test, y_pred)
nmae_test = mae / (np.max(y_test) - np.min(y_test))
mse = mean_squared_error(y_test, y_pred)
nrmse_test = np.sqrt(mse) / (np.max(y_test) - np.min(y_test))

# Calculate the evaluation metrics for training set
y_train_pred = model.predict(X_train)
y_train = y_train.reshape(-1, 1)
y_train_pred = scaler.inverse_transform(y_train_pred.reshape(-1, 1))
mae_train = mean_absolute_error(y_train, y_train_pred)
nmae_train = mae_train / (np.max(y_train) - np.min(y_train))
mse_train = mean_squared_error(y_train, y_train_pred)
nrmse_train = np.sqrt(mse_train) / (np.max(y_train) - np.min(y_train))

# Calculate the average NMAE and NRMSE
nmae_avg = np.mean([nmae_train, nmae_test])
nrmse_avg = np.mean([nrmse_train, nrmse_test])


# Print the evaluation metrics
print("NMAE Train: ", nmae_train)
print("NMAE Test: ", nmae_test)
print("Average NMAE: ", nmae_avg)
print("NRMSE TEST:",nrmse_test)
print("NRMSE Train: ", nrmse_train)
print("Average NMAE: ", nmae_avg)
# Plot the training and validation losses
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Losses')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.show()
import seaborn as sns
# Create a heatmap of the correlation matrix
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```

```
import matplotlib.pyplot as plt
import numpy as np

# Convert the actual and predicted values to a 1D numpy array
y_test = y_test.ravel()
y_pred= y_pred.ravel()

# Define the quarters and years
quarters = ['Q1', 'Q2', 'Q3', 'Q4']
start_year = 1901
end_year = 2016
year_step = 3
years = np.arange(start_year, end_year+1, year_step)

# Create a figure with subplots for each quarter
fig, axs = plt.subplots(nrows=4, ncols=1, figsize=(15, 10), sharex=True)

# Loop through each quarter and plot the actual and predicted values
for i, quarter in enumerate(quarters):
    # Get the indices for the current quarter
    quarter_indices = np.arange(i, len(years)*len(quarters), len(quarters))

    # Plot the actual and predicted values for the current quarter
    axs[i].plot(years, y_test[quarter_indices], label='Actual')
    axs[i].plot(years, y_pred[quarter_indices], label='Predicted')
    axs[i].set_title(f'Quarterly Rainfall ({quarter})')
    axs[i].set_ylabel('Rainfall (mm)')

# Add a legend and x-axis label to the bottom plot
axs[-1].set_xlabel('Year')
axs[-1].legend()

# Adjust the spacing between subplots and save the figure
plt.tight_layout()
plt.savefig('actual_vs_predicted_rainfall.png')
```

SNAPSHOTS

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 gru (GRU)                   (None, None, 256)         201216

 dropout (Dropout)           (None, None, 256)         0

 gru_1 (GRU)                 (None, None, 128)         148224

 dropout_1 (Dropout)         (None, None, 128)         0

 gru_2 (GRU)                 (None, None, 64)          37248

 dropout_2 (Dropout)         (None, None, 64)          0

 gru_3 (GRU)                 (None, 32)                9408

 dropout_3 (Dropout)         (None, 32)                0

 dense (Dense)               (None, 1)                 33

=================================================================
Total params: 396,129
Trainable params: 396,129
Non-trainable params: 0
```

Fig.2.1.Model Summery of trainable parameters based on an optimal fine-tuned GRU neural network.

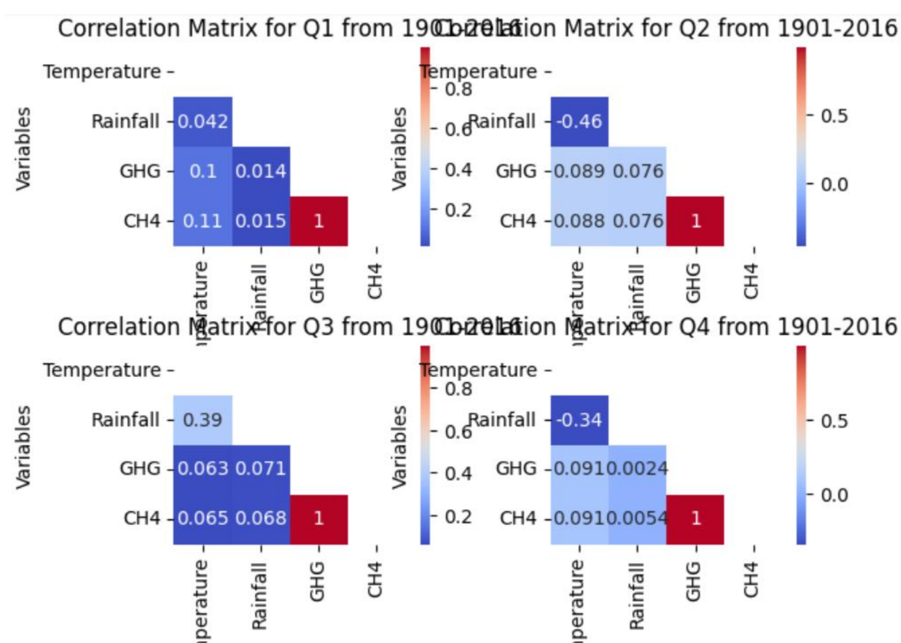


Fig. 2.2. Pearson correlation analysis of atmospheric variables on quarterly rainfall.

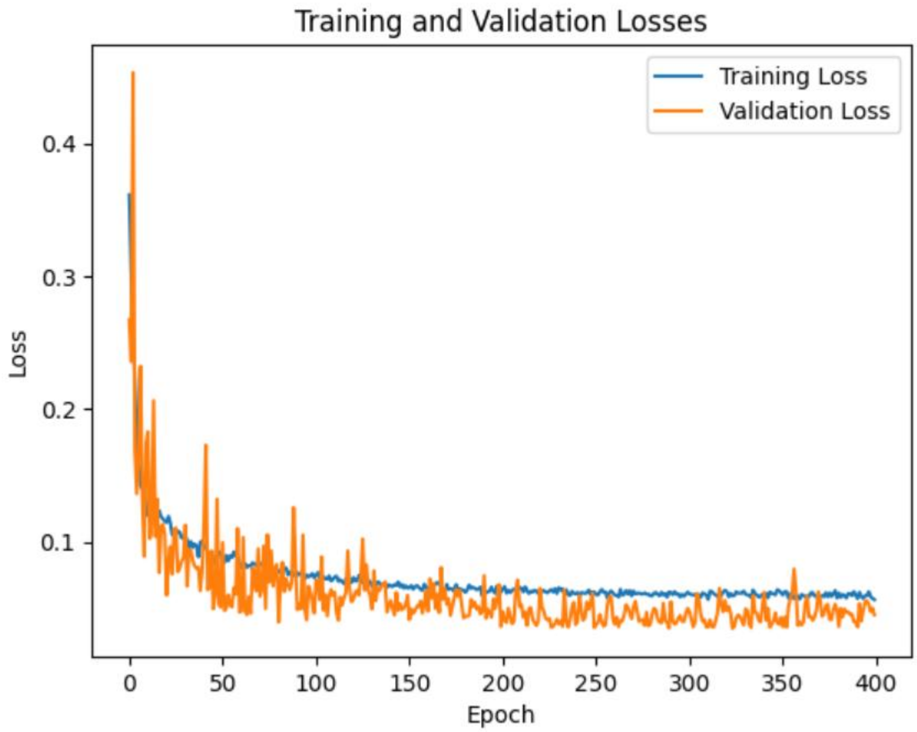


Fig. 2.3. Training and validation losses by an optimized GRU neural network based on NMAE loss function.

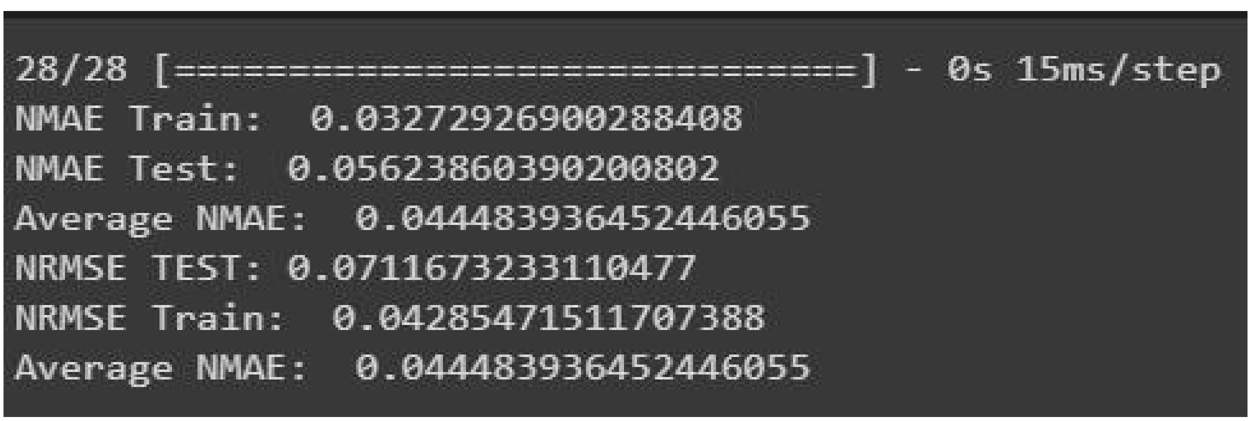


Fig.2.4. Evaluation Metrics for GRU Model Performance

```
28/28 [==============================] - 0s 14ms/step
NMAE Train:  0.038557387066068094
NMAE Test:  0.06889571769373352
Average NMAE:  0.05372655237990081
NRMSE Train:  0.04961012575061532
NRMSE Test:  0.08293960261282426
Average NRMSE:  0.05372655237990081
```

Fig.2.5. Evaluation Metrics for LSTM Model Performance

```
28/28 [==============================] - 0s 4ms/step
NMAE Train:  0.056223910776035835
NMAE Test:  0.046909833269396545
Average NMAE:  0.05156687202271619
NRMSE Train:  0.07052356567318
NRMSE TEST: 0.06276824637923487
Average NMAE:  0.05156687202271619
```

Fig.2.6. Evaluation Metrics for RNN Model Performance

```
28/28 [==============================] - 0s 3ms/step
NMAE Train:  0.04620238367415937
NMAE Test:  0.07189816723964554
Average NMAE:  0.05905027545690245
NRMSE Train:  0.057236496862694816
Average NMAE:  0.05905027545690245
```

Fig.2.7. Evaluation Metrics for DNN Model Performance

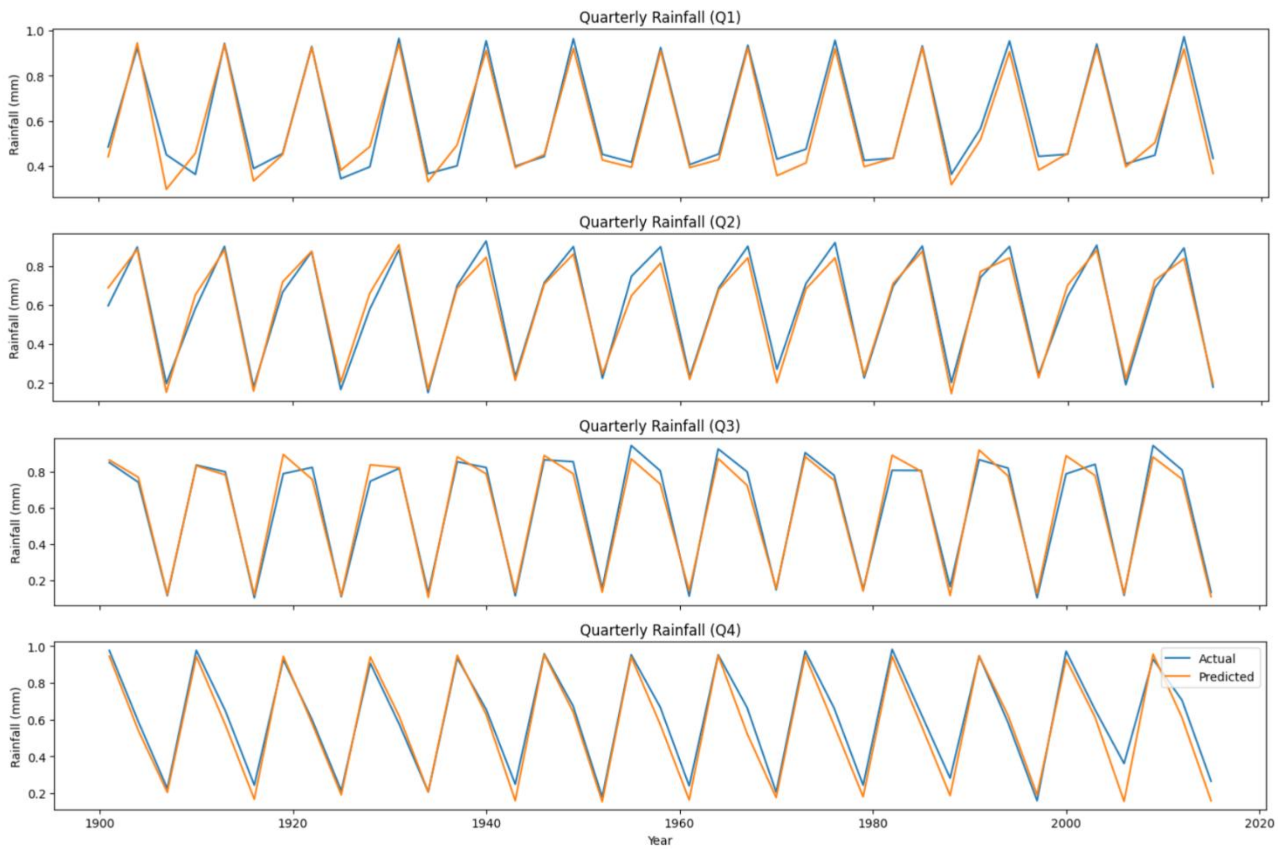


Fig.2.8. actual vs predicted rainfall

CONCLUSION AND FUTURE PLANS

The study focused on the development of a deep forecasting model using a GRU neural network to predict rainfall in Pakistan based on 30 years of atmospheric measurements. By extracting and fine-tuning ecological variables, the proposed model achieved high prediction accuracy with minimal NMAE and NRMSE compared to other rainfall forecasting models. The model demonstrated its robustness in both short-term and long-term rainfall forecasting, making it valuable for flood-prone regions like Pakistan.

Correlation and regression analyses revealed that temperature and gas emissions had varying effects on rainfall forecasting in different quarters of the year. The study validated the feasibility of the selected variables in precise rainfall forecasting, irrespective of volatile atmospheric conditions. These findings can have significant implications for disaster management institutions in taking appropriate actions and implementing effective strategies.

In future work, the researchers plan to design a hybrid approach that combines several statistical measures based on post-processed rainfall forecasts with short-term streamflow monitoring. This approach aims to overcome the limitations imposed by volatile atmospheric behavior and diverse climatic conditions. Additionally, the study intends to incorporate other forecasting algorithms, such as pretrained models and ensemble learners, to further enhance the performance of rainfall forecasting by leveraging the combined weights of each predictive model. These efforts seek to improve the accuracy and reliability of rainfall predictions, providing valuable insights for disaster management and mitigation strategies.

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BASE PAPER

Base paper: Implementing a novel deep learning technique for rainfall forecasting via Climatic variables
Year: 2023
Journal name: Science of The Total Environment
Citation Index:SCI Index
Base Paper Url:https://www.sciencedirect.com/science/article/pii/S0048969722058594
Authors: Shah Fahad, Fang Su , Sufyan Ullah Khan, Muhammad Rashid Naeem, Kailei Wei