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Climate-Based Forecasting of Dengue Dynamics

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A Deep Learning Bootcamp project
Erdős Institute's May-Summer 2024 Cohort

Overview

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Question: How can we use climate, epidemiological, and other data to forecast the dynamics of infectious diseases, e.g. dengue?

Goal: We use deep learning algorithms to analyze climate, epidemiological, and social data in order to forecast dengue dynamics, focusing on the case of Bangladesh.

Use: Policymakers can use our model to analyze or predict dengue dynamics, in order to better allocate resources and implement more effective public health measures.

Data: Climate Data , Epidemiological Data and Google Trends Data

Data preprocessing

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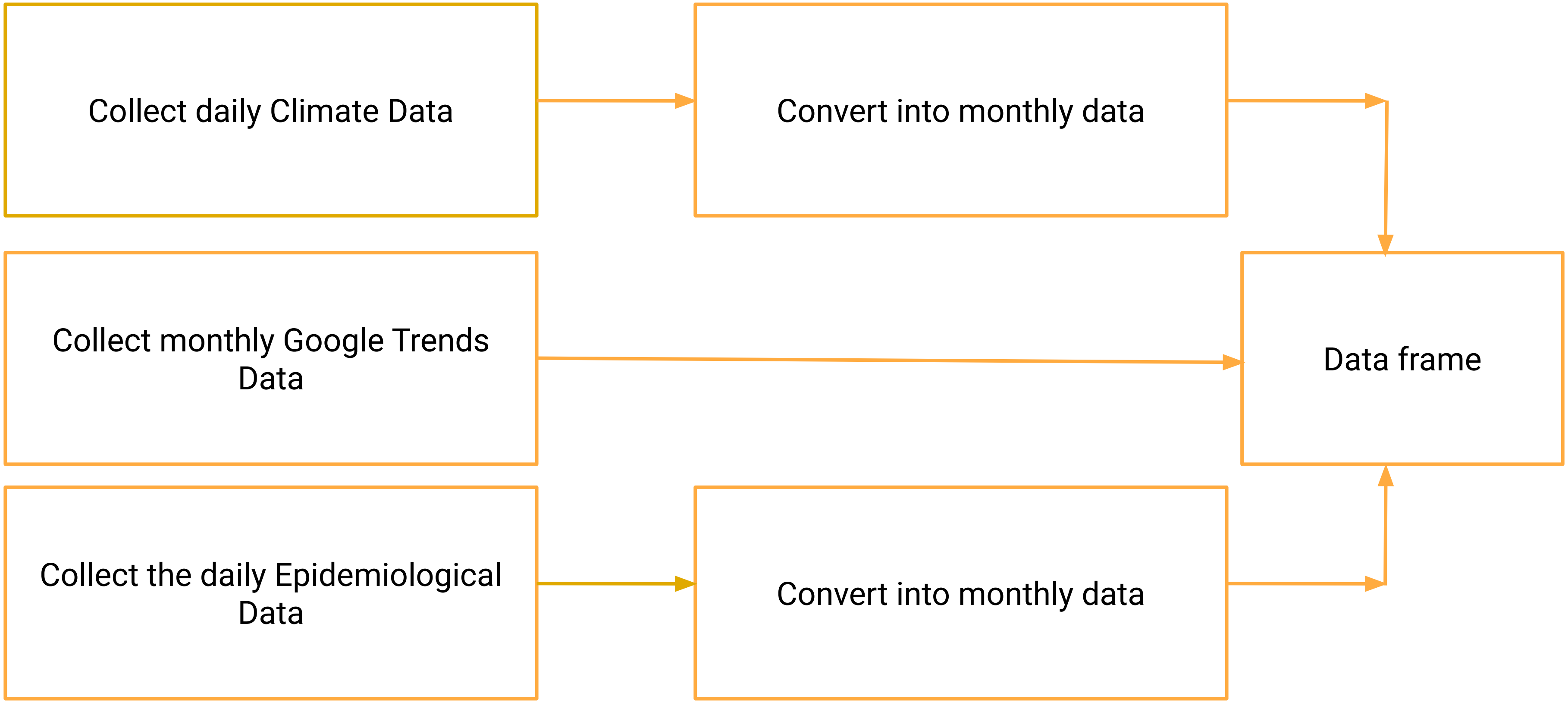

Exploratory data analysis

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```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 192 entries, 0 to 191
Data columns (total 6 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   date            192 non-null    object 
 1   temp_2m_mean    192 non-null    float64
 2   appar_temp_mean 192 non-null    float64
 3   rain_sum        192 non-null    float64
 4   goog_trends     192 non-null    int64  
 5   case            192 non-null    int64  
dtypes: float64(3), int64(2), object(1)
memory usage: 9.1+ KB
```

Exploratory data analysis


```
[ ] df.corr()
```

	date	temp_2m_mean	appar_temp_mean	rain_sum	goog_trends	case
date	1.000000	0.007473	0.031027	0.031935	0.377799	0.356004
temp_2m_mean	0.007473	1.000000	0.992262	0.845130	0.315251	0.278008
appar_temp_mean	0.031027	0.992262	1.000000	0.880395	0.316291	0.275526
rain_sum	0.031935	0.845130	0.880395	1.000000	0.216992	0.180182
goog_trends	0.377799	0.315251	0.316291	0.216992	1.000000	0.783459
case	0.356004	0.278008	0.275526	0.180182	0.783459	1.000000

Exploratory data analysis

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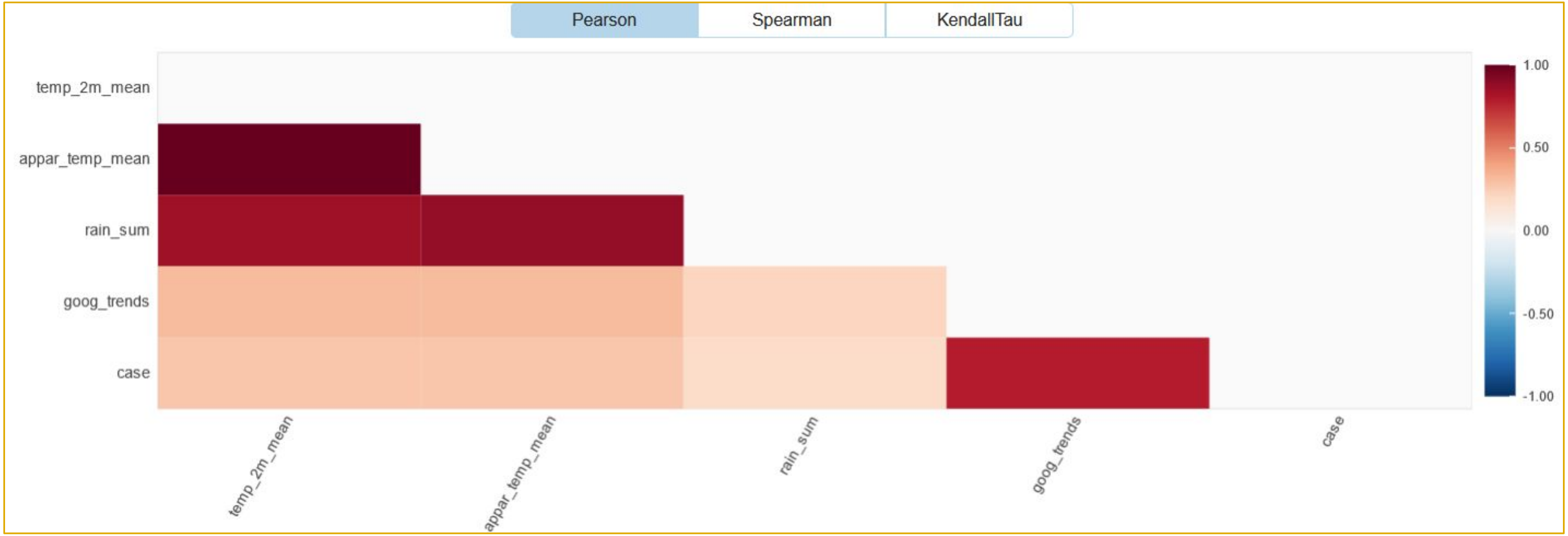

Exploratory data analysis

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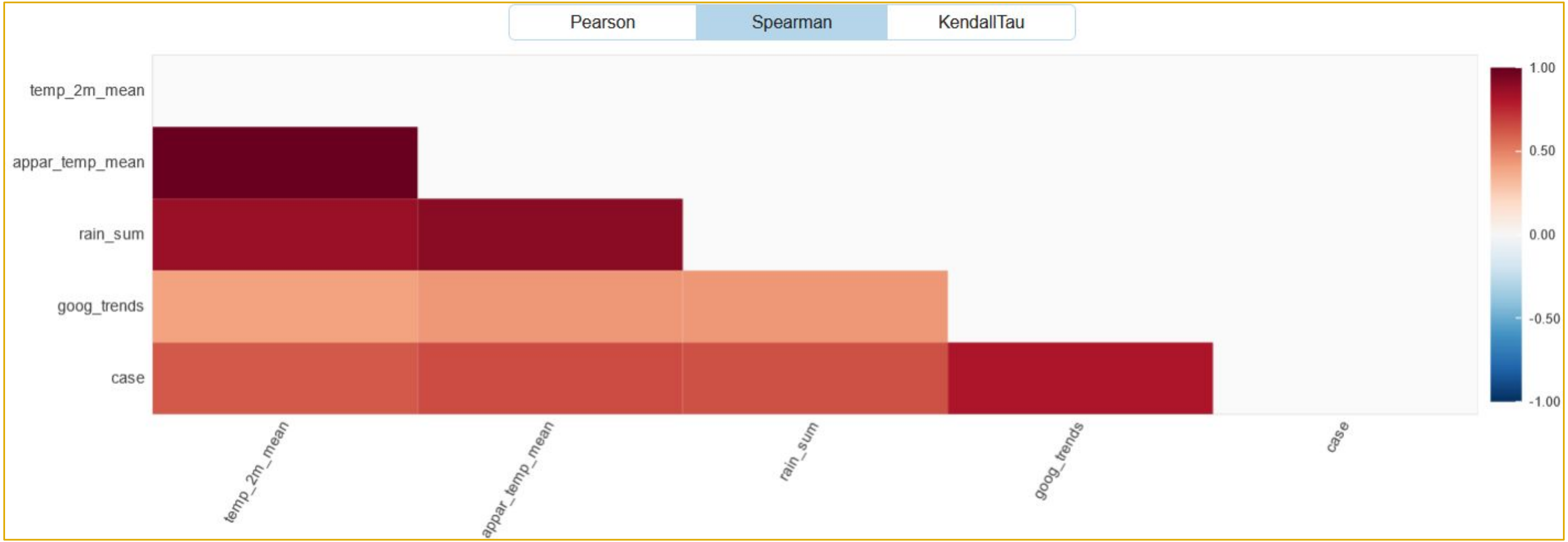

Exploratory data analysis

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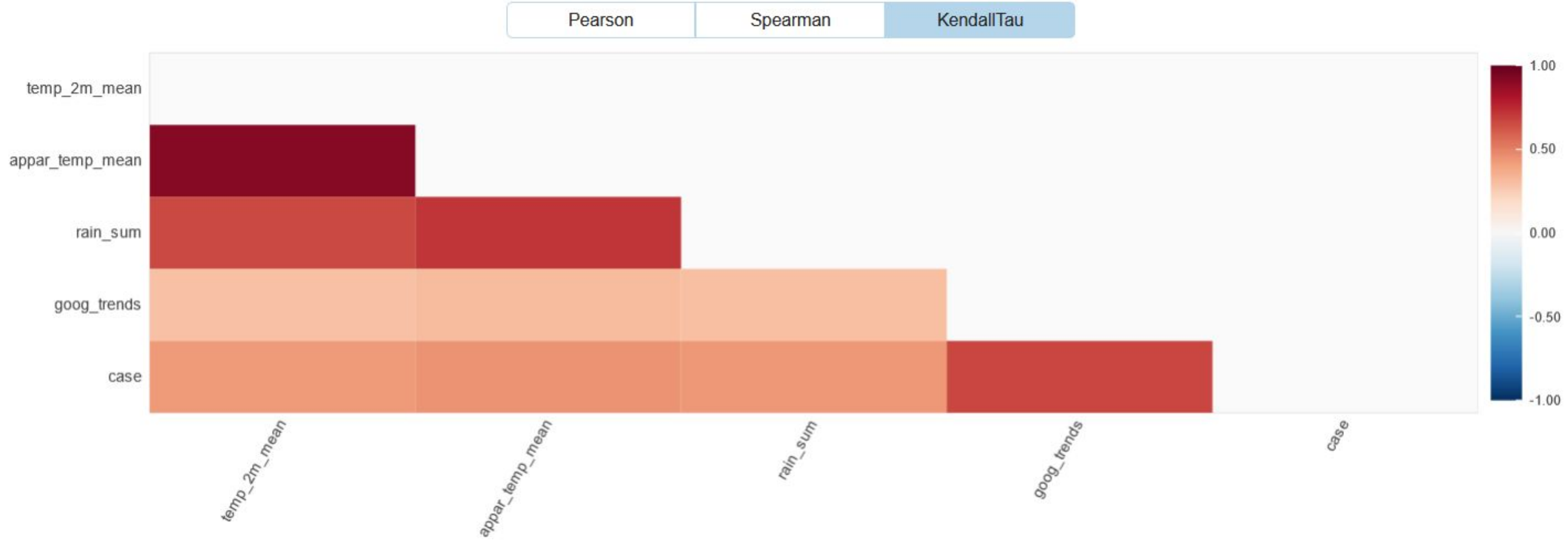
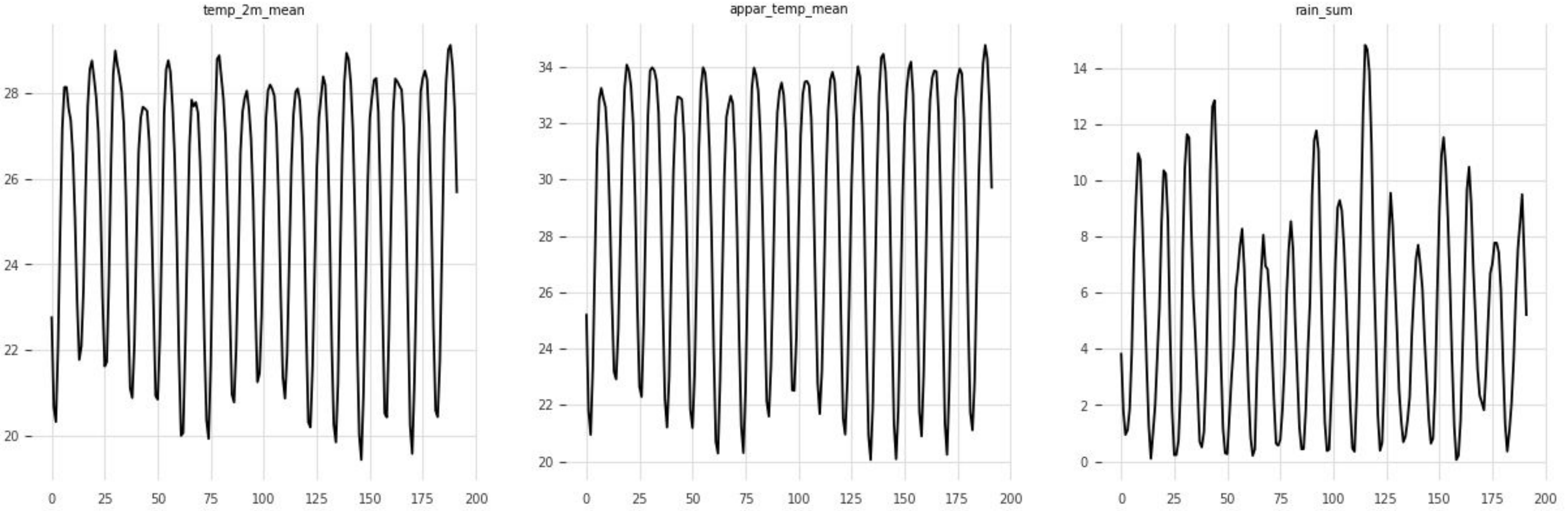


Visualizing the data

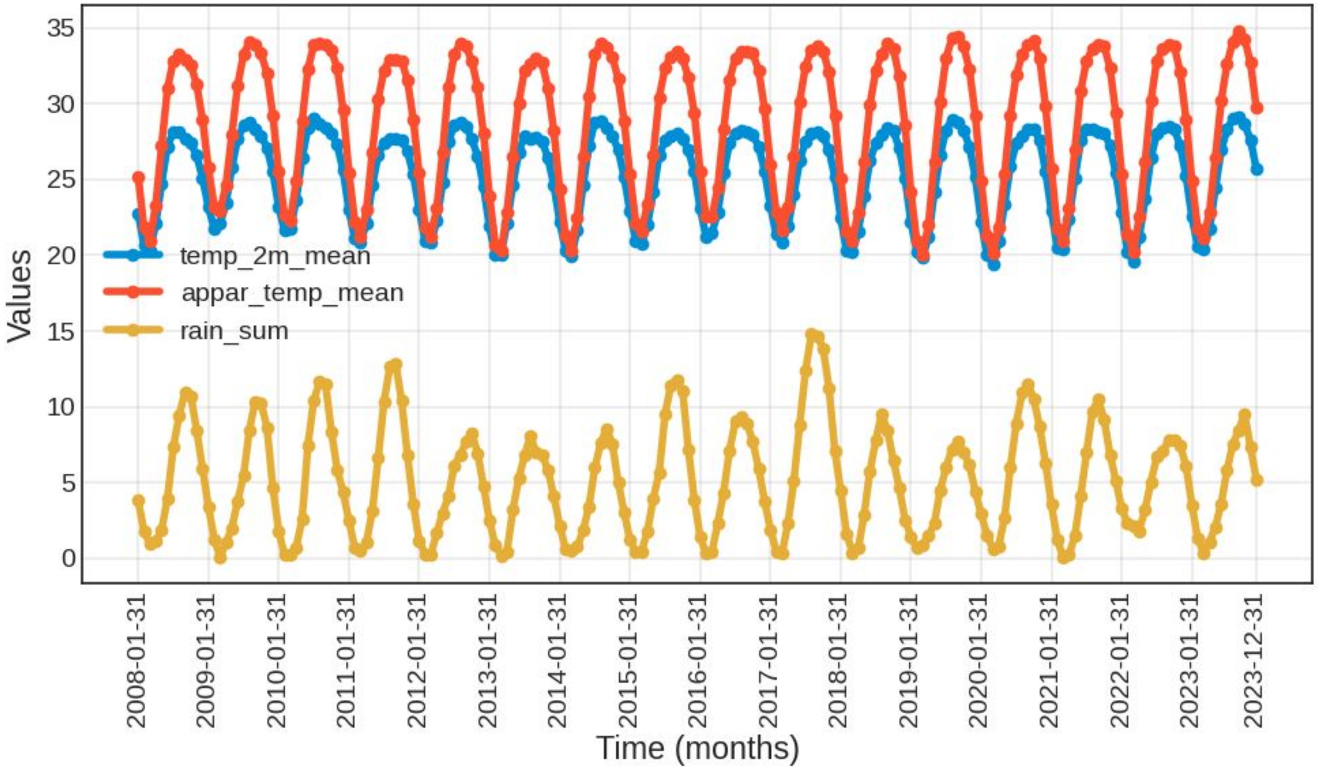


Visualizing the data

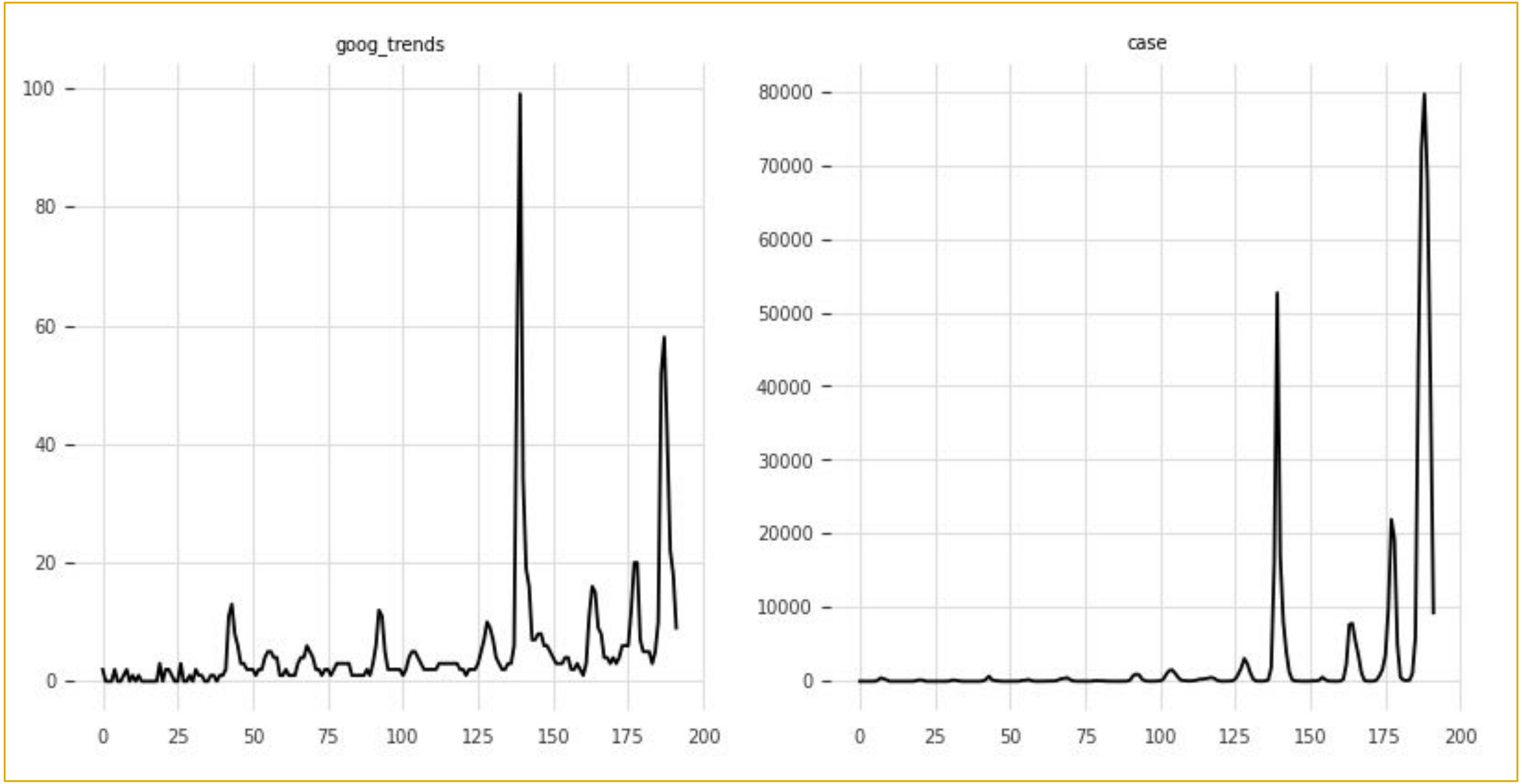
Temperature (2m)

Relative Humidity (%)

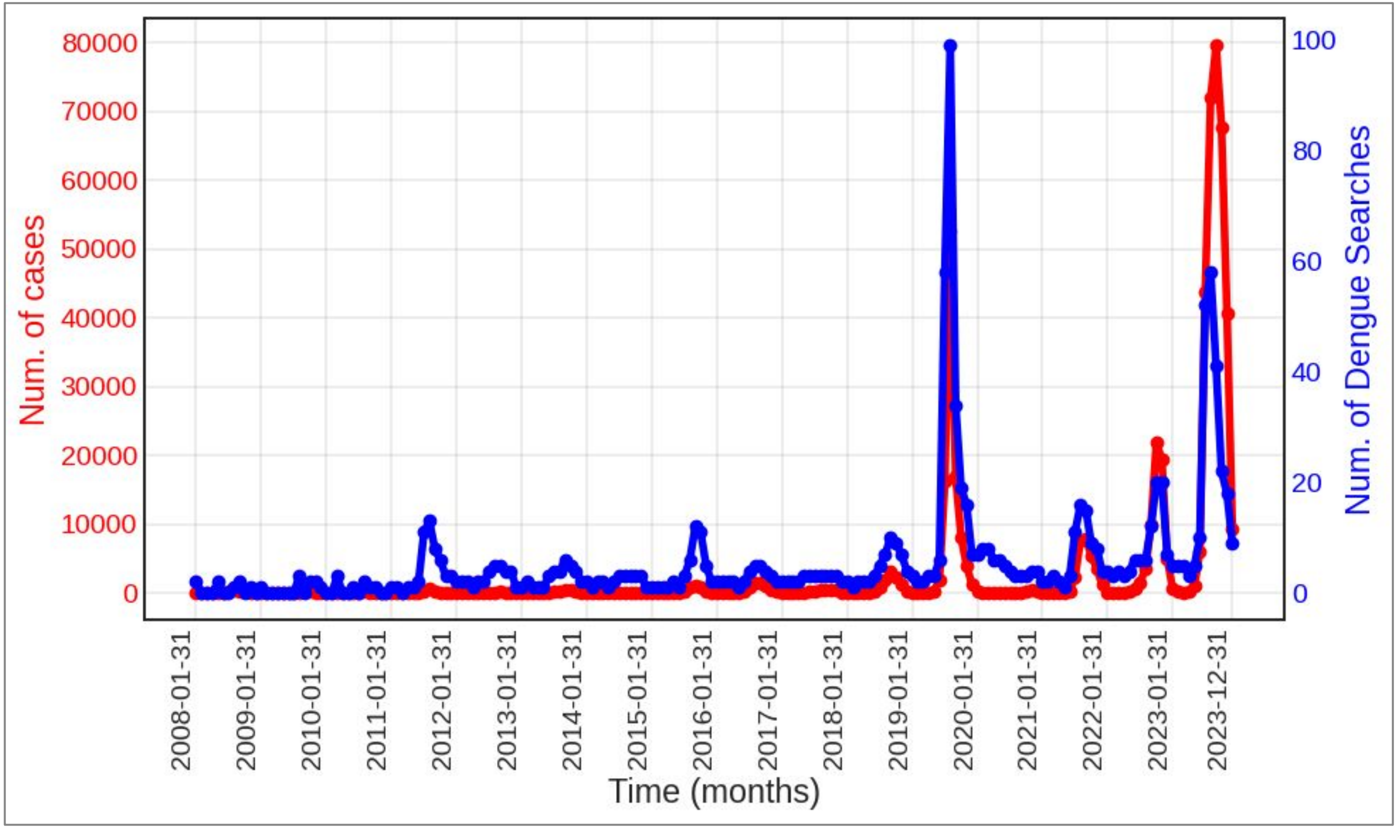
dew point 2m (degre C)



Visualizing the data



Visualizing the data



Some aspects of model training

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- Data was scaled before training for better performance
- For deep learning algorithms, hyperparameter optimization was done using a grid search or a Bayesian method (using the Optuna library)

Model building

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1. CNN
2. LSTM
3. GRU
4. Random Forest
5. XGBoost

Statistical Model: ARIMA

Model building

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1. CNN
2. LSTM
3. GRU
4. Random Forest
5. XGBoost

→ Model trained on 70%-10%-20% training-validation-test

Statistical Model: ARIMA

→ Model trained on 80%-20% training-test

Model building

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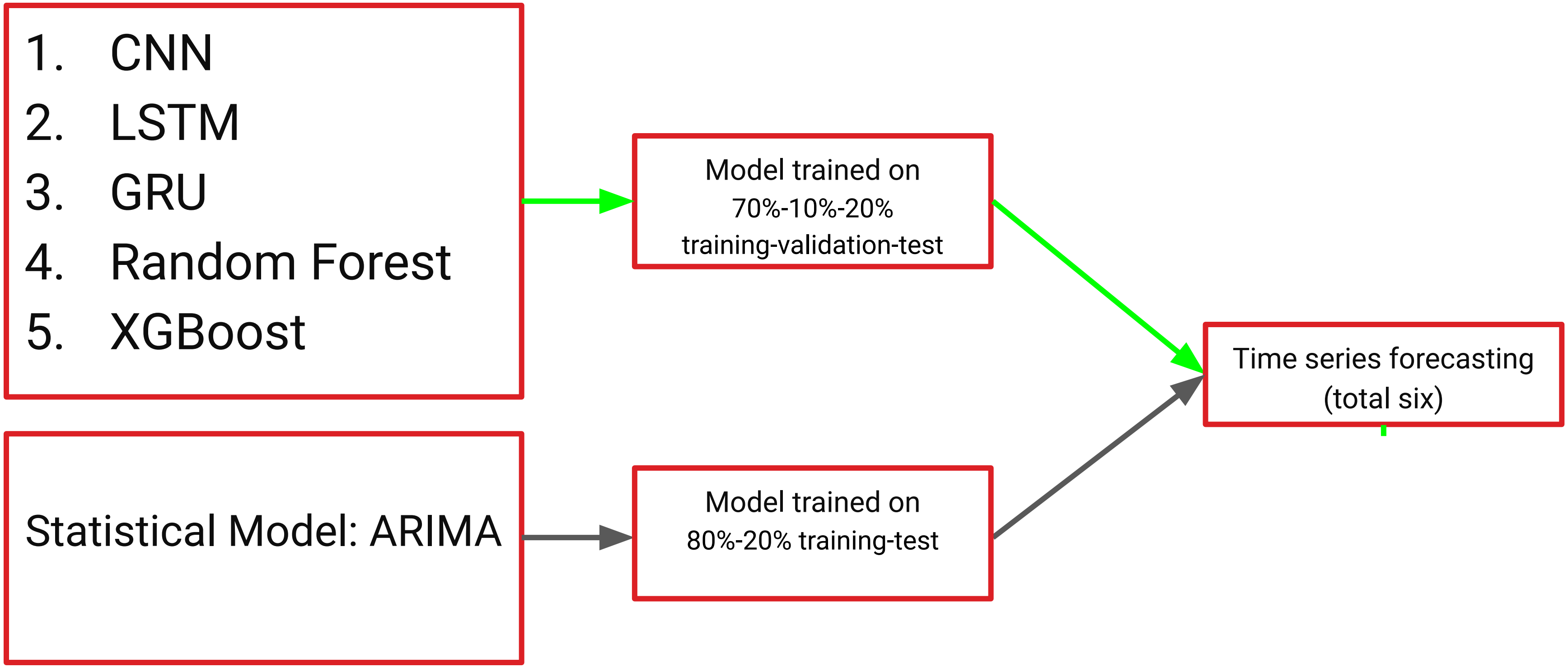

Model building

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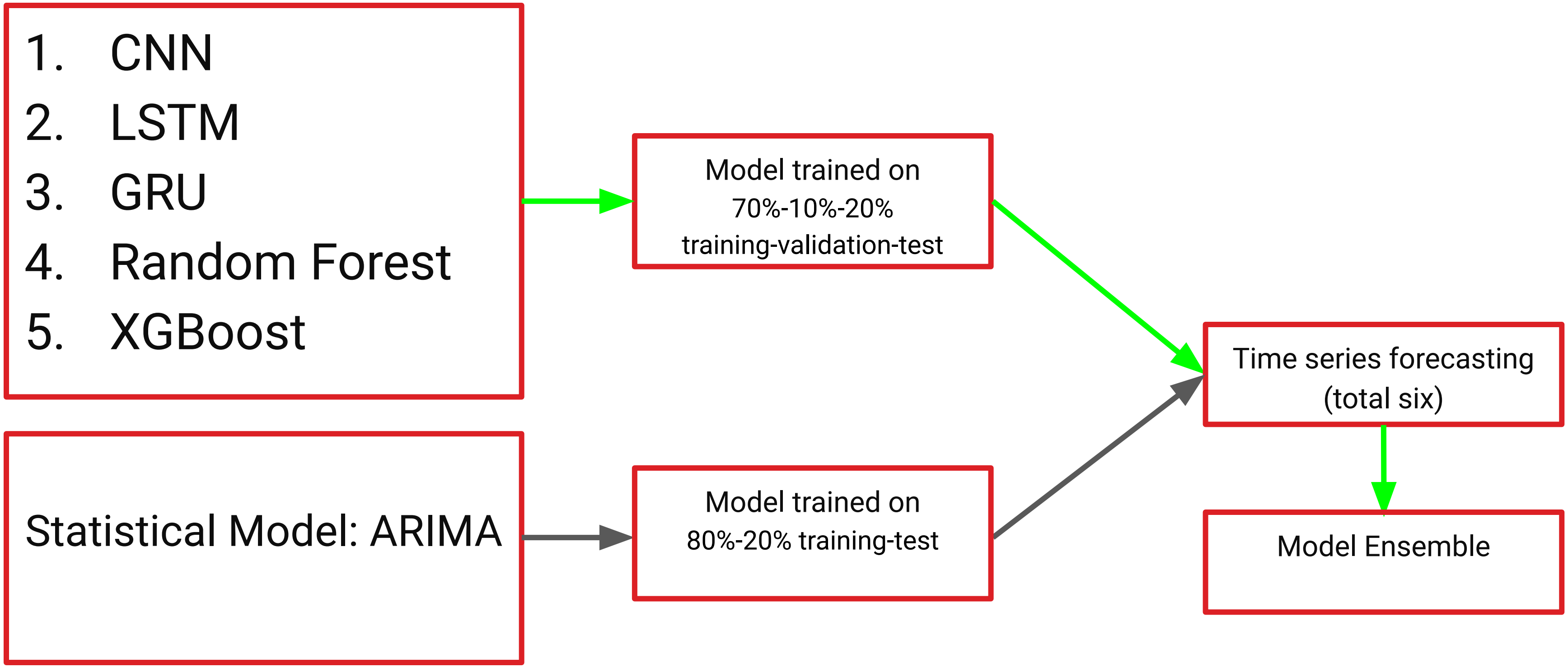
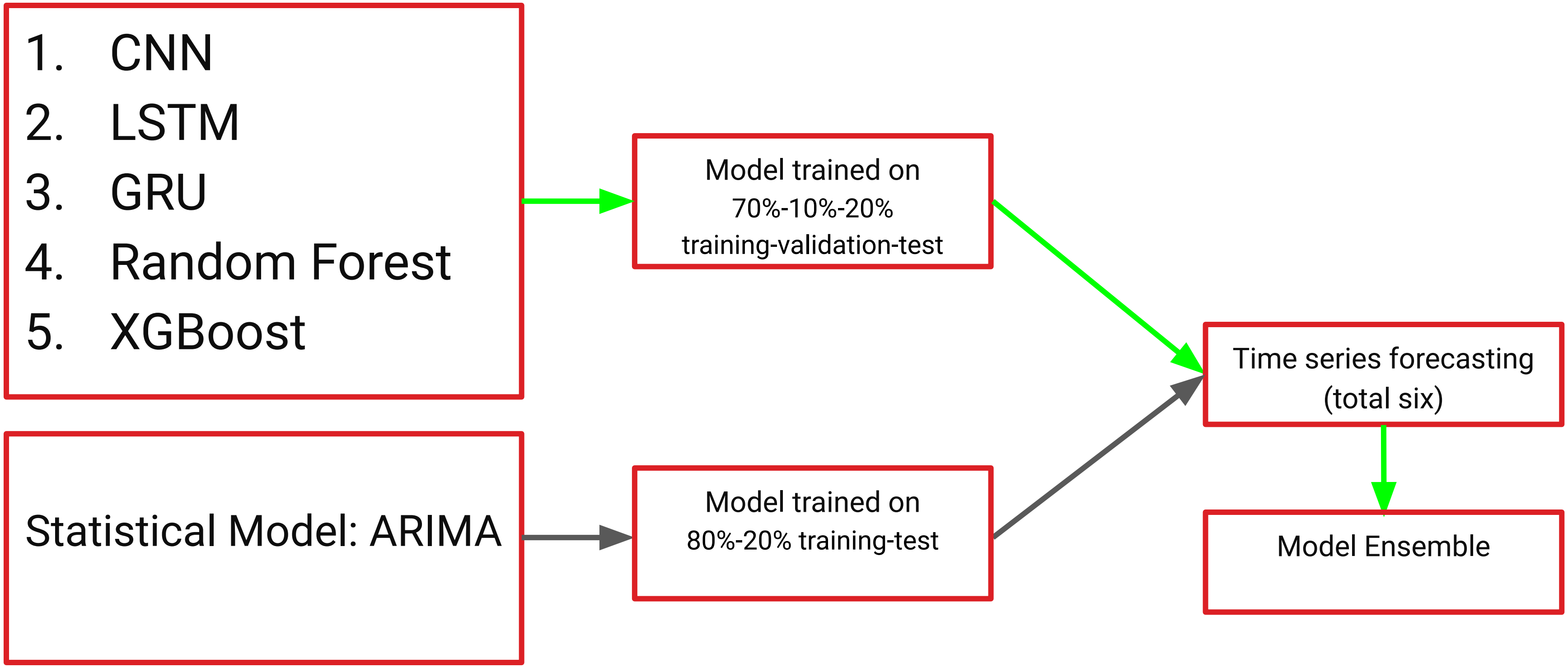


Model building



Ensemble model

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Model Predictions Using Ensemble Approach

Consider that we have RMSE scores (R_i) from M different modes. We define the penalty for each model as: $\hat{w}_i = \frac{1}{R_i}$.

We normalize these penalties to obtain the final weights w_i, which are calculated as $w_i = \frac{\hat{w}_i}{\sum_{i=1}^{M} \hat{w}_i}$.

Note that the sum

$$\sum_{i=1}^{M} w_i = \sum_{i=1}^{M} \frac{\hat{w}_i}{\sum_{j=1}^{M} \hat{w}_j} = \frac{\sum_{i=1}^{M} \hat{w}_i}{\sum_{j=1}^{M} \hat{w}_j} = \frac{\sum_{i=1}^{M} \hat{w}_i}{\sum_{i=1}^{M} \hat{w}_i} = 1$$

\subsection*{2. Compute Ensemble Predictions}

To compute the final ensemble prediction:

Let y_i represent the prediction vector from the i-th model. The final ensemble prediction vector y_{ensemble} is calculated as:
$y_{\text{ensemble}} = \sum_{i=1}^{M} w_i \mathbf{y}_i$.

Ensemble model: Forecasting

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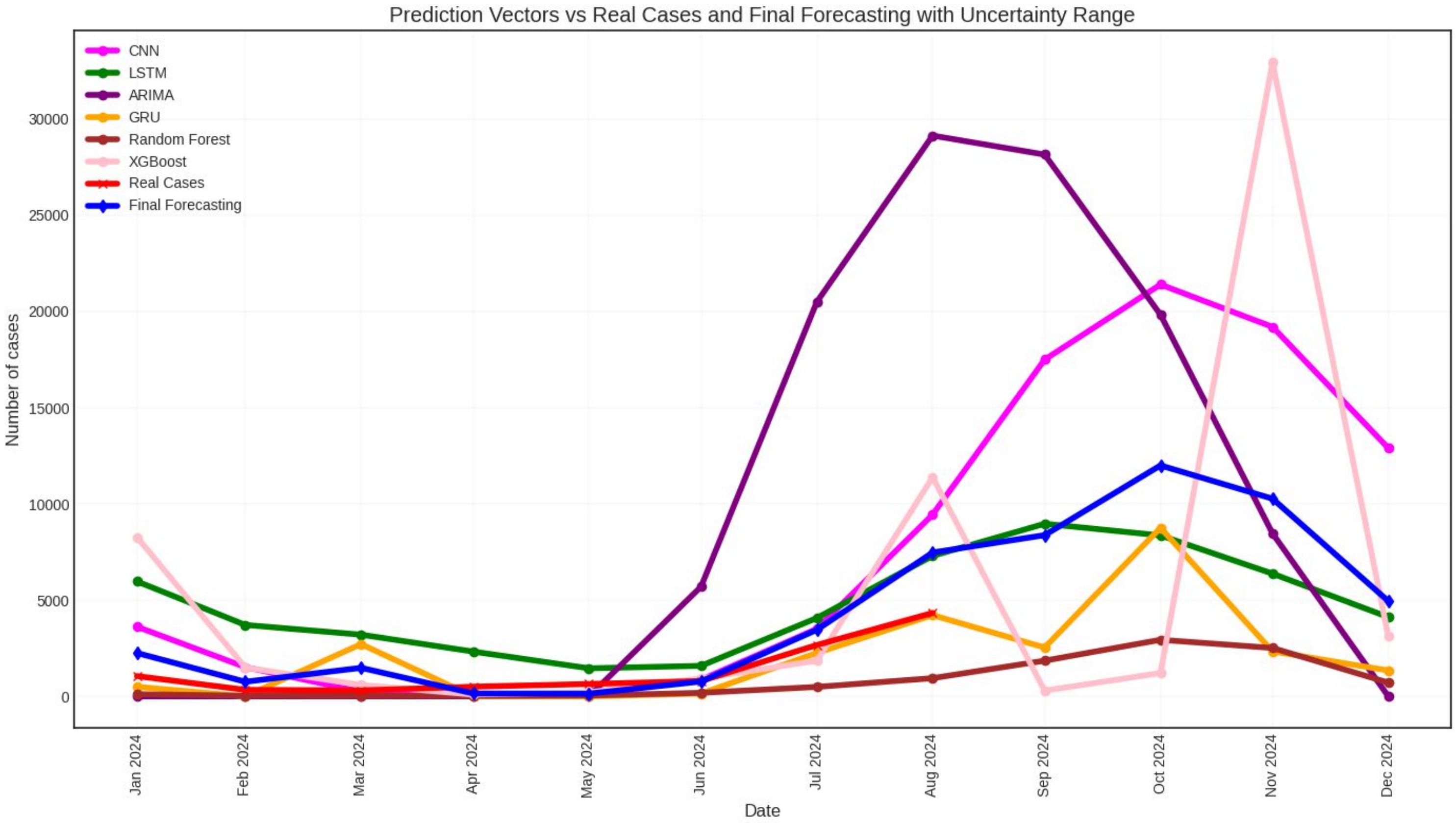

Ensemble model: Forecasting

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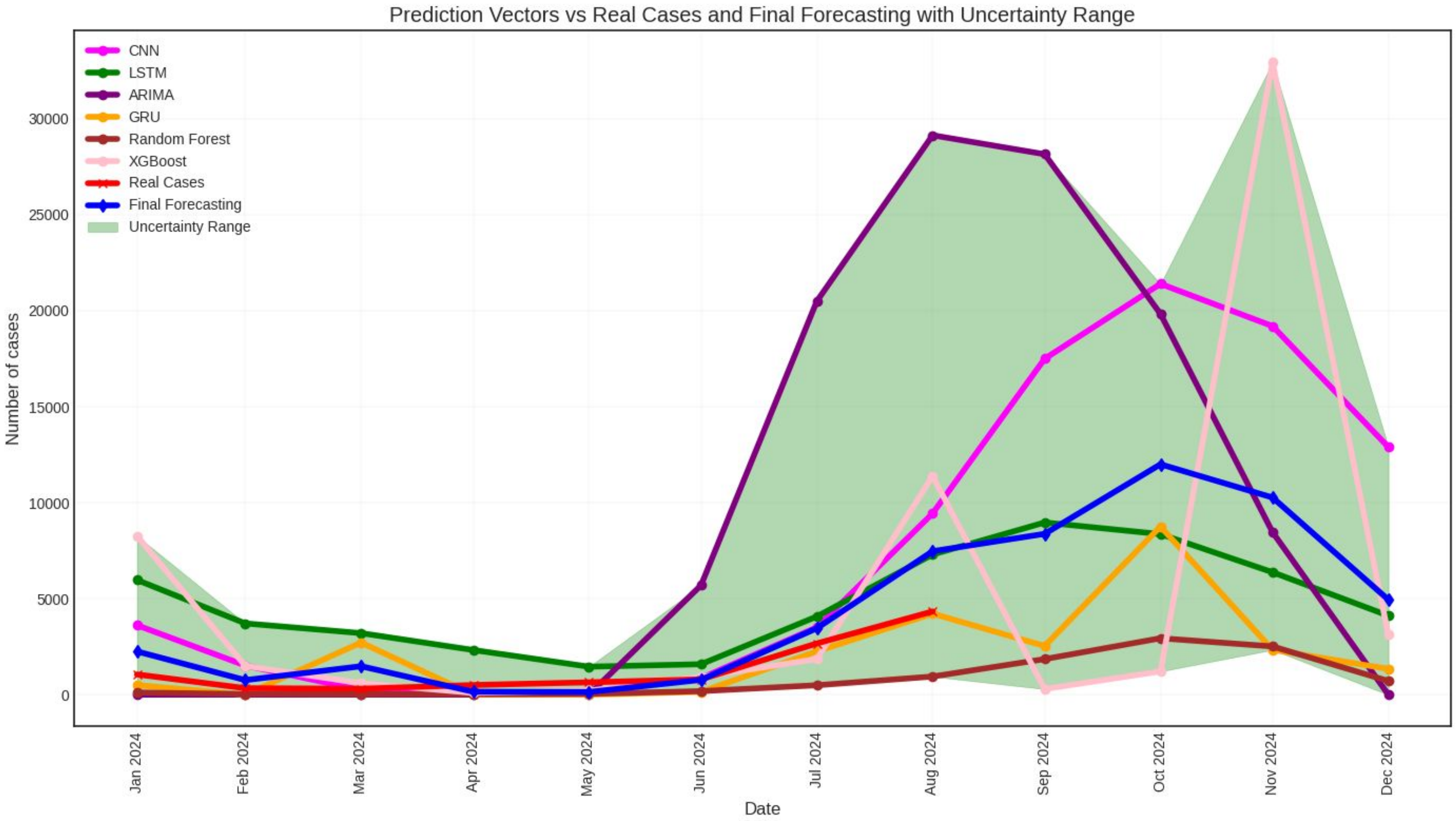
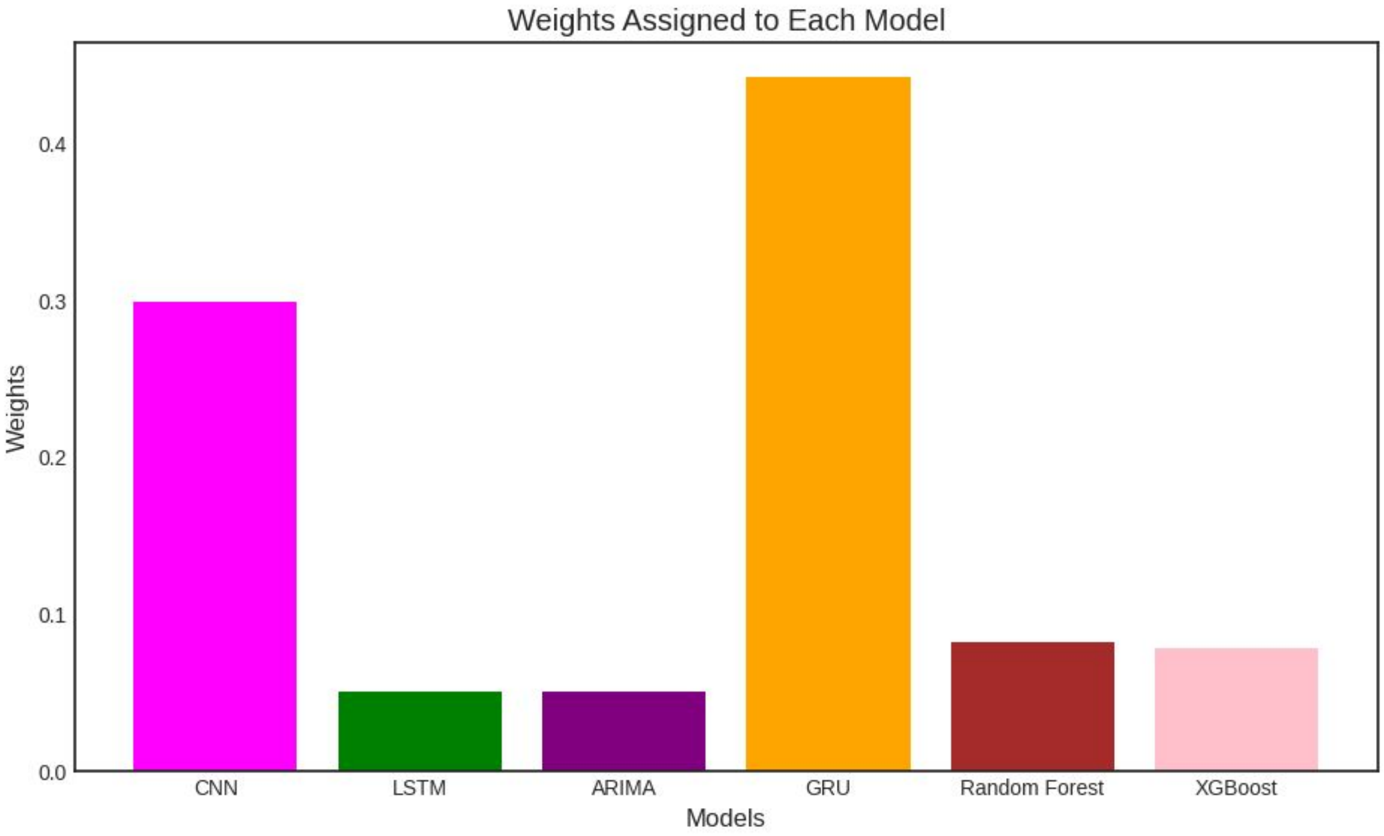


Model performance



Conclusion

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- Six deep learning and statistical models were deployed to forecast dengue dynamics in Bangladesh.
- Difficult to forecast the magnitude of the peak, but more reasonable to forecast when the peak will be and general trends
- Two models—GRU and CNN—reasonably forecast dengue cases for 2024, in terms of both test error and visual trend of forecasting in the unknown future.

Future directions

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- It remains to be explored if separating seasonal and trend components in the data improves model performance.
- Forecasting can be improved by using a bigger dataset.
- Future work will involve implementing hybrid deep learning models and sophisticated probabilistic time series forecasting algorithms.

Thank you for joining!

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