# QEarth: A Quantum AI for Climate for forecasting

Womanium Quantum+AI Project | Final Project

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# The Importance of Predicting Daily Temperatures

## Agricultural Impact

According to the Food and Agriculture Organization (FAO), accurate weather forecasts can increase crop yields by up to 20% through optimized farming practices .

## Energy Management

A study by the International Energy Agency (IEA) found that accurate temperature forecasting could reduce energy consumption by 5-10%

## Disaster Preparedness

The World Health Organization (WHO) reported that heatwaves have caused over 70,000 deaths across Europe in the past two decades alone.

# Traditional Weather Prediction

## Challenge 1

**Complexity and Computational Intensity**

Numerical weather models involve solving complex partial differential equations, which require significant computational power

## Challenge 2

**Slow Adaptation to New Data**

They are updated at fixed intervals, which limits their ability to incorporate new data and adjust forecasts dynamically.

## Challenge 3

**Linear Assumptions**

They often assume linear relationships between variables, which can oversimplify the reality of atmospheric dynamics. This can result in significant errors

# Leveraging ML for Temperature Prediction

The Power of AI/ML in Weather Prediction

Machine Learning (ML) has revolutionized the field of weather prediction by enabling the analysis of vast amounts of data to identify patterns and make accurate forecasts.

# History of ML in climate forecasting

2016

Machine Learning Applied to Weather Forecasting

2020

NOAA reported that ML forecasting models has led to a 30% reduction in the MSE

2022

According to a study by ECMWF ML models have improved the accuracy by 15-20%

2023

Comparison of machine learning techniques for weather prediction

2020

Prediction of land surface temperature of major coastal cities of India using bidirectional LSTM neural networks

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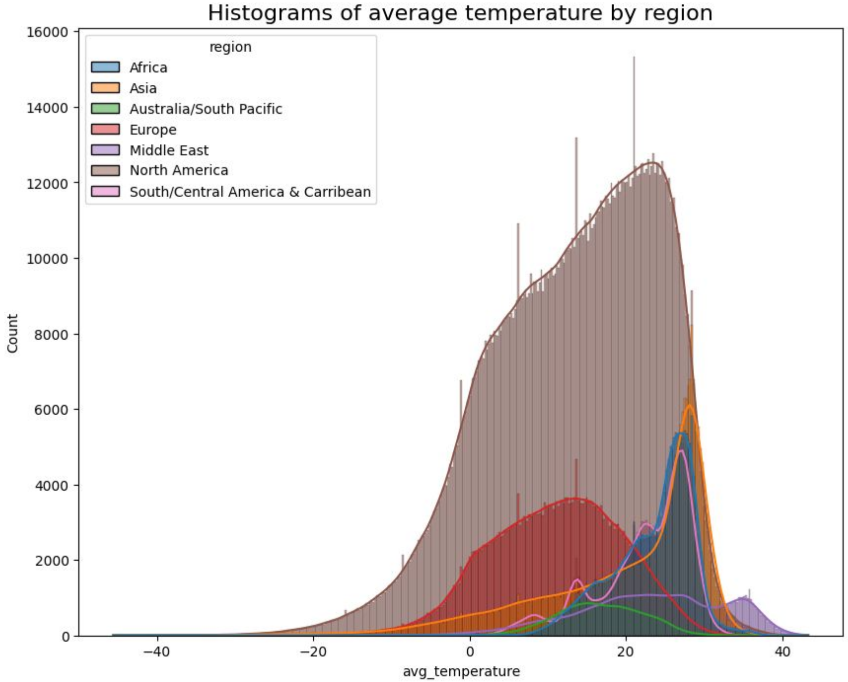
# Dataset

Daily Temperature of Major Cities

# Daily Temperature of Major Cities

- ➔ This dataset contains historical daily temperature data for major cities across the world. The data is collected over several years and provides a comprehensive view of temperature variations in various urban areas.

- ➔ Number of Records: Approximately 2.5 million rows of temperature data.



# Data Preprocessing

## Data Cleaning

- ➔ Handling Missing Values
- ➔ Duplicate Removal

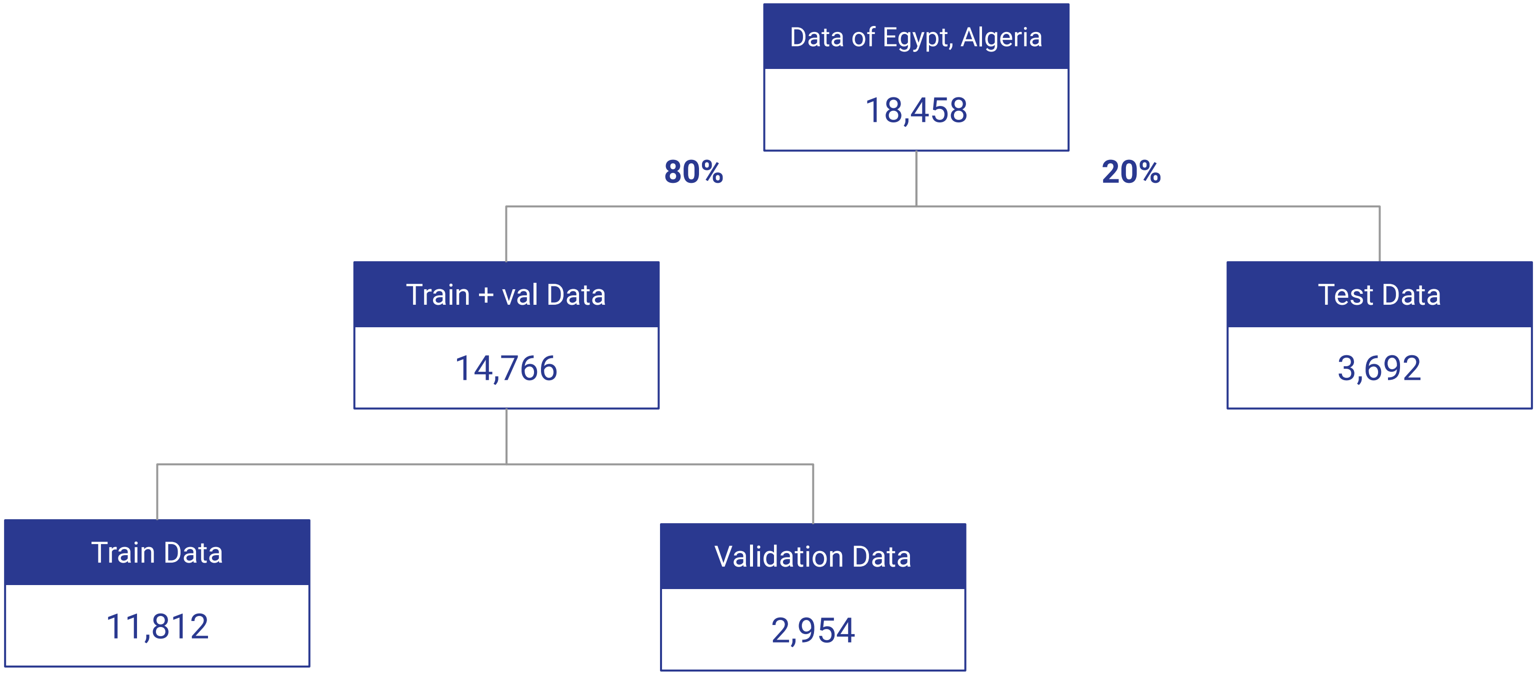
## Enhanced Feature Representation

- ➔ Columns Encoded as each feature is transformed into a binary feature representing its presence or absence.
- ➔ Increase feature from 8 to 73

## Data Transformation

- ➔ Date Parsing: Convert date strings to datetime
- ➔ Convert Temperature unit

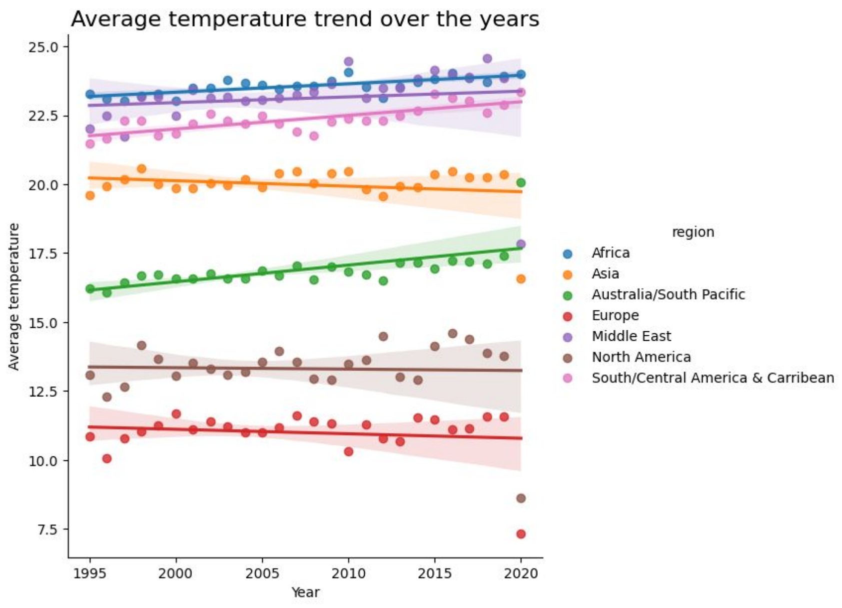
# Data Splitting



# Linear regression

➔ After thorough analysis, we identified that the core task is to predict continuous temperature values, making it a regression problem. This involves predicting a numeric outcome based on historical data.

➔ We plotted linear regression lines for various regions, showing how temperature trends evolve over time.



# Implementations

# Baseline Model

## Long Short-Term Memory

# Long Short-Term Memory

- Inspired by the approach used in the paper "Prediction of Land Surface Temperature of Major Coastal Cities of India Using Bidirectional LSTM Neural Networks." This study demonstrated the effectiveness of LSTM models in predicting temperature variations in coastal regions.

- LSTM is a type of Recurrent Neural Network (RNN) particularly well-suited for time series data, making it a popular choice for weather forecasting tasks.

- Its ability to capture long-term dependencies in sequential data allows it to model the complex temporal patterns found in climate and temperature data effectively.

# LSTM Performance

**Our work**

- ➔ $R^2$ (Coefficient of Determination): 0.89
- ➔ Mean Squared Error (MSE): 1.25°C²
- ➔ Mean Absolute Error (MAE): 0.04°C
- ➔ Root Mean Squared Error (RMSE): 0.41°C

**Prediction of Land Surface Temperature of Major Coastal Cities of India Using Bidirectional LSTM Neural Networks**

- ➔ $R^2$ (Coefficient of Determination): 0.84
- ➔ Mean Squared Error (MSE): 1.04°C²
- ➔ Mean Absolute Error (MAE): 0.64°C
- ➔ Root Mean Squared Error (RMSE): 0.45°C

# LSTM Performance

## Prediction of Land Surface Temperature of Major Coastal Cities of India Using Bidirectional LSTM Neural Networks

**Table 6** | Overview of ML model's performance measures for each major coastal city

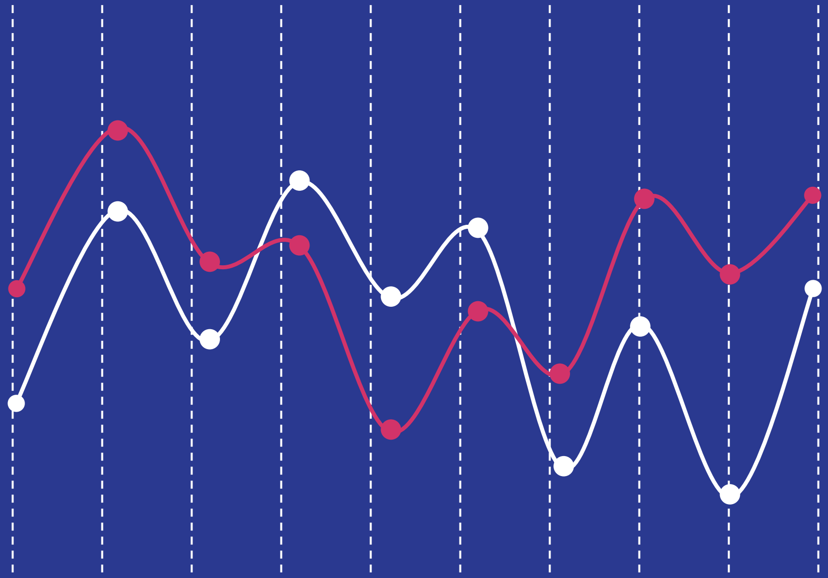
| City | Model | MSE | MAE | $R^2$ | NSE | Norm | RSR | PBIAS |
|---|---|---|---|---|---|---|---|---|
| Chennai | ANN | 1.78 | 1.03 | 0.74 | 0.66 | 90.30 | 0.58 | 3.00 |
| | RNN | 0.89 | 0.55 | 0.87 | 0.85 | 63.89 | 0.39 | 1.15 |
| | LSTM | 1.06 | 0.64 | 0.84 | 0.80 | 69.77 | 0.45 | 0.82 |
| | BiLSTM | 1.04 | 0.64 | 0.84 | 0.80 | 69.23 | 0.45 | 1.19 |

## Our work

```
Out[45]:
    Text(500, 1.25, 'Mean Absolute Error :0.04')
```

# Support Vector Machines

Support Vector Machine for regression



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# Support Vector Regression

- ➔ Support Vector Regression (SVR) extends the principles of SVM to regression tasks. SVR aims to predict continuous outcomes rather than classifying data.

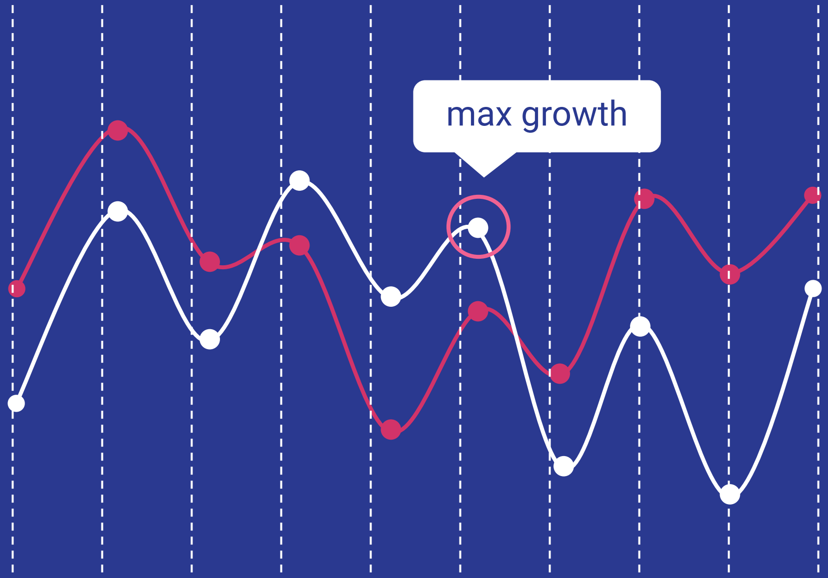
- ➔ The use of kernel functions allows SVM and SVR to model complex relationships and handle a wide range of data types.

- ➔ Results

```
R^2: 0.87
Mean Absolute Error: 1.03
Mean Squared Error: 0.3
Root Mean Squared Error: 0.38
```

# Quantum Support Vector Machines

Support Vector Machine for regression



# Quantum Support Vector Regression

- Quantum algorithms can potentially process large datasets and perform complex computations more quickly than classical algorithms. This speedup is particularly advantageous for high-dimensional data and complex models, where classical SVM may face limitations.
- Quantum Support Vector Regression (QSVR) leverages the unique capabilities of quantum computing to enhance the performance of traditional support vector regression methods.

# Results of QSVR

| Hardware | Accuracy |
|---|---|
| ibm_osaka | 0.93215454211545 |
| ibm_sherbrooke | 0.92864372115432 |
| ibm_brisbane | 0.93451239874561 |

# Results discussion

# Results Discussion

## LSTM

The LSTM model's performance closely aligns with the results from the paper baseline

## SVR

The SVR model performed better compared to the LSTM model. This improvement indicates SVM's potential in achieving lower errors and better accuracy in this dataset.

## QSVR

The QSVR model yielded results almost identical to the classical SVR model. This similarity in performance is attributed to the simulation environment used for QSVR, rather than Quantum hardware.

# Future Scope

# Limitations and challenges

- ➔ The primary challenge faced was the lack of access to real quantum hardware. The project was constrained to using quantum computing simulations rather than actual quantum machines. This limitation affected the ability to fully leverage quantum computing's potential advantages and to obtain real-world performance metrics.

- ➔ The availability of GPU resources was limited during the project. The small GPU quota restricted the ability to run large-scale experiments, train complex models, and process extensive datasets efficiently.

- ➔ Due to working alone, The project had a strict timeline, which restricted the time available for in-depth experimentation, model refinement, and migration of work to real quantum hardware.

**Access to Quantum Hardware**

**Computational Resources**

**Time Constraints**

# Thank you