PRESERVING CULTURAL HERITAGE SITES THROUGH RANDOM FOREST AND XGBOOST ALGORITHM FOR MICROCLIMATE MONITORING AND PREDICTION

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PRESERVING CULTURAL HERITAGE SITES THROUGH RANDOM FOREST AND XGBOOST ALGORITHM FOR MICROCLIMATE MONITORING AND PREDICTION

IMAN AIDI ELHAM BIN HAIRUL NIZAM

A thesis submitted in fulfilment of the
requirements for the award of the degree of
Bachelor of Computer Science (Software Engineering)

School of Computing
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DEDICATION

This thesis is dedicated to my parents who taught me to work hard and dream big in life. Thank you to my supervisor Associate Prof Dr Mohd Shahizan Othman for guiding me throughout this thesis. Thank you too to my supportive friends who are also struggling to finish their own thesis and has helped me with this thesis either physically or morally.

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ABSTRACT

The preservation of heritage architecture is significant in maintaining the cultural heritage of a region. This study focuses on the development of a machine learning-based microclimate monitoring system to assist local authorities in Johor Bahru, Malaysia, with planning preventive maintenance actions for a designated heritage site. The research project comprises obtaining microclimate data, including temperature, rainfall, humidity, and wind speed from the Copernicus Climate Data Store (CDS). To optimize the monitoring and prediction process, the performance of two machine learning algorithms, Random Forest and XGBoost, will be compared to determine the most suitable method for microclimate analysis. The project also involves designing and developing a dashboard that displays the analysis of historical microclimate data and prediction using data visualization tools. The effectiveness of the developed algorithm and dashboard will be assessed to evaluate their potential in aiding local authorities with the implementation of more effective maintenance plans for the heritage site. This research aims to contribute to the preservation of cultural heritage sites by utilizing advanced machine learning techniques for microclimate monitoring and prediction, supporting sustainable and efficient conservation efforts.

ABSTRAK

Pemeliharaan senibina warisan memegang peranan penting dalam mengekalkan warisan budaya suatu kawasan. Kajian ini memberi tumpuan kepada pembangunan sistem pemantauan mikroiklim berasaskan pembelajaran mesin untuk membantu pihak berkuasa tempatan di Johor Bahru, Malaysia, merancang tindakan penyelenggaraan pencegahan untuk tapak warisan yang ditetapkan. Projek penyelidikan ini merangkumi mendapatkan data mikroiklim, termasuk suhu, taburan hujan, kelembapan, dan kelajuan angin, daripada Copernicus Climate Data Store (CDS). Untuk mengoptimumkan proses pemantauan dan ramalan, prestasi dua algoritma pembelajaran mesin, Random Forest dan XGBoost akan dibandingkan untuk menentukan kaedah yang paling sesuai untuk analisis mikroiklim. Projek ini juga melibatkan reka bentuk dan pembangunan papan pemuka yang memaparkan data mikroiklim masa nyata menggunakan alat visualisasi data. Keberkesanan algoritma dan papan pemuka yang dibangunkan akan diuji untuk menilai potensi mereka dalam membantu pihak berkuasa tempatan melaksanakan rancangan penyelenggaraan yang lebih berkesan untuk tapak warisan. Penyelidikan ini bertujuan untuk menyumbang kepada pemeliharaan tapak warisan budaya dengan menggunakan teknik pembelajaran mesin yang maju untuk pemantauan dan ramalan mikroiklim, yang pada akhirnya menyokong usaha-usaha konservasi yang mampan dan cekap.

TABLE OF CONTENTS

TITLE		PAGE
	DECLARATION	**i**
	DEDICATION	**ii**
	ACKNOWLEDGEMENT	**iii**
	ABSTRACT	**iv**
	ABSTRAK	**v**
	TABLE OF CONTENTS	**vi**
	LIST OF TABLES	**ix**
	LIST OF FIGURES	**x**
	LIST OF ABBREVIATIONS	**xi**
CHAPTER 1	**INTRODUCTION**	**1**
1.1	Overview	1
1.2	Problem Background	2
1.3	Research Aim	2
1.4	Research Objectives	3
1.5	Research Scopes	3
1.6	Research Contribution	4
1.7	Report Organization	5
CHAPTER 2	**LITERATURE REVIEW**	**7**
2.1	Introduction to Case Study	7
2.2	Importance of Preserving Cultural Heritage Sites	8
2.3	Impact of Microclimate Factors on Cultural Heritage Sites	8
2.4	Traditional Methods for Cultural Heritage Sites Preservation	9
2.5	Machine Learning Algorithms	10
	2.5.1 Random Forest	11
	2.5.2 XGBoost	13

2.6 Comparative Analysis of Previous Case Studies and the Uses of Machine Learning in Cultural Heritage Preservation 14

2.7 Implementation of Random Forest and XGboost in Microclimate Monitoring and Prediction 16

2.7.1 Comparison Between Random Forest and XGBoost Algorithms 17

2.8 Chapter Summary 18

CHAPTER 3 RESEARCH METHODOLOGY 21

3.1 Introduction **Error! Bookmark not defined.**

3.2 Research Workflow **Error! Bookmark not defined.**

3.2.1 Phase 1: Literature Review**Error! Bookmark not defined.**

3.2.2 Phase 2: Data Requirement and Data Collection **Error! Bookmark not defined.**

3.2.3 Phase 3: Machine Learning Model Development **Error! Bookmark not defined.**

3.2.4 Phase 4: Dashboard Development**Error! Bookmark not defined.**

3.3 Justification of Tools, Techniques and Data**Error! Bookmark not defined.**

3.3.1 Preservation of Cultural Heritage**Error! Bookmark not defined.**

3.4 Data-Driven Decision Making **Error! Bookmark not defined.**

3.5 Efficiency and Cost-Effectiveness**Error! Bookmark not defined.**

3.6 Real-Time Monitoring and Visualization**Error! Bookmark not defined.**

3.7 Stakeholder Engagement and Collaboration**Error! Bookmark not defined.**

3.8 Chapter Summary **Error! Bookmark not defined.**

CHAPTER 4 RESEARCH DESIGN AND IMPLEMENTATION Error! Bookmark not defined.

4.1 Introduction **Error! Bookmark not defined.**

4.2 Proposed Solution **Error! Bookmark not defined.**

4.3 Research Area Zone Mapping **Error! Bookmark not defined.**

4.4 Experiment Design **Error! Bookmark not defined.**

4.4.1 Microclimate Data Collection Process **Error! Bookmark not defined.**

4.4.2 Pre-processing and Feature Extraction of Microclimate Data **Error! Bookmark not defined.**

4.4.3 Splitting of Data into Training and Testing Sets **Error! Bookmark not defined.**

4.4.4 Training and Evaluation of Machine Learning Models **Error! Bookmark not defined.**

4.5 Parameter and Testing Methods **Error! Bookmark not defined.**

4.5.1 Parameters to be Measured **Error! Bookmark not defined.**

4.5.1.1 Prediction Accuracy **Error! Bookmark not defined.**

4.5.1.2 Mean Absolute Error **Error! Bookmark not defined.**

4.5.1.3 Mean Squared Error **Error! Bookmark not defined.**

4.5.2 Testing Procedure **Error! Bookmark not defined.**

4.5.2.1 Splitting Data **Error! Bookmark not defined.**

4.5.2.2 Model Evaluation **Error! Bookmark not defined.**

4.5.2.3 Calculation of Evaluation Metrics **Error! Bookmark not defined.**

4.5.2.4 Analysis and Interpretation **Error! Bookmark not defined.**

4.6 Chapter Summary **Error! Bookmark not defined.**

CHAPTER 5 CONCLUSION AND RECOMMENDATIONS 51

5.1 Research Outcomes 51

5.2 Contributions to Knowledge 52

5.3 Future Works 53

REFERENCES 55

LIST OF TABLES

TABLE NO.	TITLE	PAGE
Table 1:	Comparative Analysis of Previous Case Studies and the Uses of Machine Learning in Cultural Heritage Preservation	15
Table 2:	List of Difference between Random Forest and XGBoost Algorithms	17

LIST OF FIGURES

FIGURE NO.	TITLE	PAGE
Figure 1:	Random Forest Model Architecture	11
Figure 2:	XGBoost Model Architecture	13
Figure 3:	Research Workflow	**Error! Bookmark not defined.**
Figure 4:	Area of Research Zone	**Error! Bookmark not defined.**
Figure 5:	Import necessary libraries	**Error! Bookmark not defined.**
Figure 6:	Read the microclimate data from a CSV file	**Error! Bookmark not defined.**
Figure 7:	(Pre-processing) Handle missing values using mean imputation and standardize the data	**Error! Bookmark not defined.**
Figure 8:	(Feature Engineering) Extract relevant features using SelectKBest with f_regression as the scoring function	**Error! Bookmark not defined.**
Figure 9:	Split the pre-processed data into training and testing sets	**Error! Bookmark not defined.**
Figure 10:	Train and evaluate the Random Forest and XGBoost algorithms	**Error! Bookmark not defined.**

LIST OF ABBREVIATIONS

ML	-	Machine Learning
AI	-	Artificial Intelligence
RF	-	Random Forest
CH	-	Cultural Heritage
CSV	-	Comma-separated Values
LR	-	Logistic Regression
ANN	-	Artificial Neural Network
CNN	-	Convolutional Neural Network
KNN	-	K-Nearest Neighbour
XGBoost	-	Extreme Gradient Boosting

CHAPTER 1

INTRODUCTION

1.1 Overview

Cultural heritage sites are the basis for our global and historical values. They connect us to the traditions left by our ancestors and contribute significantly to the cultural identity of human society (Lombardo et al., 2020). The preservation of cultural heritage, whether it be buildings or artifacts, is subject to various risks of damage and deterioration that result from microclimate conditions in the surrounding environment. These conditions are determined by several factors, including microclimate parameters such as temperature, humidity, airborne pollutants concentrations, air speed, and others (Fabbri & Bonora, 2021). Particularly in developing nations, these impacts pose a significant challenge to the preservation of cultural heritage (Pioppi et al., 2020). Safeguarding worldwide cultural heritage sites is of utmost importance for preserving cultural identity and human heritage, as well as promoting cultural and tourism-driven economic development (Alcaraz Tarragüel et al., 2012).

In recent years, the administration of cultural heritage sites and monuments has gained worldwide focus through the implementation of detection, monitoring, and comprehensive assessment methods. Initiatives are also underway to enhance and preserve these heritage resources by adopting suitable adaptation measures and sustainable management approaches (Guzman et al., 2020). To address these challenges, this thesis focuses on the application of advanced machine learning algorithms, namely Random Forest and XGBoost, for microclimate monitoring and prediction at cultural heritage sites. By leveraging these techniques, it aims to contribute to the preservation of cultural heritage sites under changing environmental conditions, supporting sustainable and efficient conservation efforts.

1.2 Problem Background

Cultural heritage sites have consistently drawn visitors who seek to spend quality time and pursue unique experiences by engaging with local cultures and communities (Ramkissoon et al., 2013). As a result, the economies of these tourist destinations largely rely on attracting visitors, encouraging repeat visits, garnering recommendations, and generating positive word-of-mouth regarding the locations (Rezapouraghdam et al., 2021). In addition, the natural environments in which tourism activities occur are also enhancing the well-being and quality of life for residents (Ramkissoon et al., 2018). Lately, Johor Bahru has been experiencing frequent climate fluctuations that negatively impact the aesthetic appeal of the area's heritage sites, significantly affecting the industry of tourism and local economy. Generally, microclimate changes in these regions cause substantial damage to cultural heritage sites and various monuments. Consequently, striking a balance between consumption and conservation strategies presents increasing challenges for the effective management of cultural heritage sites (Buonincontri et al., 2017). Therefore, focusing on the preservation of cultural heritage and promoting sustainable tourism has become a primary objective recently to support both cultural heritage tourism and the overall well-being of communities (Megeirhi et al., 2020).

1.3 Research Aim

The goal of this study is to analyze vulnerable zones of cultural heritage sites and monuments in Johor Bahru, Malaysia, by employing microclimate monitoring and prediction through the Random Forest and XGBoost algorithms. By assessing temperature, rainfall, humidity, and wind speed, the study aims to maintain environmental sustainability at these heritage sites. In this research, we have prepared a microclimate monitoring dashboard and evaluated the significance of factors contributing to microclimate changes. The Random Forest and XGBoost algorithms were employed to analyze the impact of these factors on the preservation of cultural heritage sites.

1.4 Research Objectives

The following are the objectives proposed:

(a) To investigate and identify the most suitable machine learning algorithms for analyzing microclimate data, recognize patterns, trends, and predictions related to the heritage site's preservation.

(b) To evaluate the accuracy of the developed machine learning models and the dashboard in assisting local authorities to plan preventive maintenance actions that preserve the site's aesthetics and cultural values.

(c) To develop and design a dashboard that displays microclimate data trends and predictions.

1.5 Research Scopes

The scope of this research project covers several aspects related to the preservation of the Sultan Ibrahim Building in Johor Bahru and A Famosa in Melaka using machine learning-based microclimate prediction. The primary focus is on the development of the machine learning algorithm and dashboard to collect, display, and analyze microclimate parameters for assisting the local authority in planning preventive maintenance actions for these two heritage sites. Specific areas included in the scope of this research are:

(a) Research involves obtaining microclimate data from the Copernicus Climate Data Store (CDS) for a designated heritage site in Johor Bahru and Melaka. This data contains parameters like temperature, rainfall, humidity, and wind speed.

(b) The research intends to compare the performance of two different machine learning algorithms between Random Forest and XGBoost to determine the most suitable method for microclimate monitoring and prediction.

(c) The project includes designing and developing a dashboard by using HTML and JavaScript that display the analysis of historical microclimate data.

(d) The research will involve evaluating the accuracy of the developed algorithm and dashboard in assisting local authorities with planning more effective maintenance plans for the heritage site.

1.6 Research Contribution

A thorough literature review on microclimate impacts on cultural heritage sites reveals that many researchers have used various statistical and machine learning methods, including Logistic Regression (LR), Artificial Neural Network (ANN), Convolutional Neural Network (CNN), K-Nearest Neighbor (KNN), and Support Vector Machine (SVM), to create microclimate monitoring and prediction dashboards. However, the combination of Random Forest and XGBoost algorithms, along with the analysis of temperature, humidity, and wind speed, has not yet been employed in the context of heritage site preservation. As a result, this study offers a novel contribution to the machine learning field, particularly for modeling microclimate threats and risk assessments of cultural heritage sites.

In the context of the current changing climate and landscape, this study is highly relevant and makes a significant contribution to sustainable management of cultural heritage resources. Climate change can pose a significant threat to the integrity of heritage sites due to its impact on key environmental factors such as temperature, rainfall, humidity, and wind patterns. This can lead to increased vulnerability and potential damage to these cultural assets. The study offers valuable insights and technical guidance regarding the appropriate machine learning algorithms, and proper interpretation and evaluation of outcomes, which can inform future research and decision-making processes.

Moreover, this study has essential implications for the conservation of natural resources and heritage sites in Johor Bahru and Melaka. The findings of this study are expected to have practical applications for professionals involved in land use planning, landscape management, archaeological preservation, and public administration, as they strive to effectively manage cultural heritage sites and promote environmental sustainability through evidence-based strategies. By monitoring and predicting microclimate changes using Random Forest and XGBoost algorithms, stakeholders can better preserve and protect cultural heritage sites for future generations.

1.7 Report Organization

This report comprises five chapters. Chapter 1 introduces the topic of preserving cultural heritage sites through microclimate monitoring and prediction using Random Forest and XGBoost algorithms, the research background, and the purpose of conducting this study in Johor Bahru and Melaka. Chapter 2 discusses the literature review related to microclimate monitoring, the assessment of temperature, rainfall, humidity, and wind speed, as well as the comparison of machine learning techniques for processing and analyzing data from heritage sites. Chapter 3 delves into methodology of the research, describing how the study is conducted using the Random Forest and XGBoost algorithms to measure and analyze the data on temperature, rainfall, humidity, and wind speed for preserving cultural heritage sites. Chapter 4 presents the research design and implementation, detailing how the experiment was executed to extract valuable insights from the microclimate data. Chapter 5 showcases the results obtained from this research, including the dashboard displaying the analyzed data. Finally, Chapter 6 offers a summary and conclusion for the study, highlighting the key findings and implications for the preservation of cultural heritage sites through microclimate monitoring and prediction using Random Forest and XGBoost algorithms.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction to Case Study

Climate change has emerged as a significant global challenge in recent years, impacting various sectors, including the preservation of cultural heritage sites. The increasing frequency and intensity of extreme weather events, along with gradual shifts in temperature, humidity, and wind patterns, have highlighted the need for adaptive solutions to safeguard these invaluable assets.

One promising approach to address these challenges involves the application of advanced algorithms, such as Random Forest and XGBoost, for microclimate monitoring and prediction at cultural heritage sites. These techniques can help preserve and protect these valuable assets by analysing temperature, humidity, and wind speed data, which are crucial factors in the conservation of these sites.

This case study focuses on the implementation of Random Forest and XGBoost algorithms for microclimate monitoring and prediction at two cultural heritage sites in Johor Bahru which is Sultan Ibrahim Building and another heritage site in Melaka which is A Famosa. By leveraging these advanced techniques and developing dashboards for data visualization and analysis, this research aims to enhance the understanding of site-specific microclimates and inform effective conservation strategies for these historic landmarks.

Through continuous assessment and refinement of these methods, researchers, conservators, and heritage site managers can work together to develop improved strategies for preserving cultural heritage sites like Sultan Ibrahim Building and A Famosa under changing environmental conditions. By adopting a collaborative approach, we can ensure the protection and preservation of these invaluable assets for future generations to appreciate and learn from, even in the face of challenges posed by climate change.

2.2 Importance of Preserving Cultural Heritage Sites

The preservation of cultural heritage sites holds immense significance for society, history, and identity, as these sites serve as tangible reminders of our shared past, providing valuable insights into the cultural, social, and economic development of human civilizations (Lowenthal, 1985). By protecting and maintaining these sites, we ensure the continuity of our cultural memory and allow future generations to appreciate and learn from the rich tapestry of human history (UNESCO, 1972). Moreover, cultural heritage sites contribute to a sense of belonging and pride within communities, fostering social cohesion and promoting intercultural dialogue (Smith, 2006). Furthermore, preserving these sites can offer economic benefits, as they often attract tourism and stimulate local economies (Timothy & Boyd, 2003). Given these multifaceted advantages, it is crucial to develop and implement strategies to safeguard cultural heritage sites against various threats, including the impact of microclimate factors, to ensure their longevity and continued cultural relevance.

2.3 Impact of Microclimate Factors on Cultural Heritage Sites

Microclimate factors, such as humidity, rainfall, temperature and wind speed play a significant role in the deterioration of cultural heritage sites. Existing studies have established the adverse effects of these factors on various materials and structures, leading to both physical and chemical degradation (Cassar, 2005; Camuffo, 2014).

Temperature fluctuations, especially in the presence of moisture, can lead to the expansion and contraction of materials like stone, brick, and mortar, resulting in cracks, delamination, and structural damage (Camuffo, 2014). Moreover, extreme temperatures can accelerate the decay of organic materials, such as wood and textiles, commonly found in cultural heritage sites (Cassar, 2005).

Humidity is another critical factor in the deterioration process. High humidity levels can cause moisture to accumulate in porous materials, leading to the growth of mold and bacteria, which can weaken and damage the structure (Lankester & Brimblecombe, 2012). Additionally, the presence of moisture can facilitate the dissolution of soluble salts in porous materials, causing efflorescence and sub florescence, further compromising structural integrity (Cassar, 2005).

Wind speed, particularly in combination with rain, can exacerbate the erosion of building materials and increase the rate of material loss from structures (Cassar, 2005). Moreover, high wind speeds can cause physical damage to fragile elements, such as decorative features and stained-glass windows (Camuffo, 2014).

In summary, understanding the impact of microclimate factors on cultural heritage sites is crucial for developing effective preservation strategies. By identifying and mitigating the risks associated with these factors, we can better protect these invaluable resources and ensure their continued existence for future generations.

2.4 Traditional Methods for Cultural Heritage Sites Preservation

Traditional methods for cultural heritage site preservation often rely on reactive maintenance approaches. These approaches involve responding to issues and damage after they have already occurred, rather than anticipating and preventing them. Reactive maintenance has several limitations, making it necessary to explore initiative-taking and preventive measures for the preservation of cultural heritage sites (Staniforth, 2013).

Delayed intervention is one of the limitations of reactive maintenance, as it occurs after the damage has been detected, leading to further deterioration or irreversible loss of cultural elements (Muñoz Viñas, 2002). Additionally, reactive maintenance can be expensive, especially if the damage requires extensive interventions and specialized expertise (Stovel, 2005). Incomplete recovery can also be an issue, as advanced damage can result in the loss of original features or materials, compromising the site's authenticity and historical value (Muñoz Viñas, 2002).

Moreover, interventions during reactive maintenance can be invasive or destructive, leading to further damage or exposing other areas to new risks (Matero, 1999).

To address these limitations, there is a need to shift towards initiative-taking and preventive measures, such as regular monitoring, preventive conservation, maintenance planning, and capacity building for local stakeholders. Regular inspections and monitoring can help identify early signs of deterioration or potential threats (Caple, 2008), while preventive conservation can reduce or eliminate risk factors contributing to the site's deterioration, such as controlling humidity and temperature (Muñoz Viñas, 2002). Maintenance planning, including preventive measures and timely interventions, can also help address potential issues (Caple, 2008). Capacity building through training and education for local stakeholders can further enhance the site's preservation efforts (Ashley-Smith, 2016).

In conclusion, the preservation of cultural heritage sites requires a shift towards initiative-taking and preventive measures, which can minimize the risk of irreversible damage, maintain the site's authenticity and historical value, and reduce the overall cost of preservation efforts. By adopting regular monitoring, preventive conservation, maintenance planning, and capacity building for local stakeholders, cultural heritage sites can be better preserved for future generations (Muñoz Viñas, 2002; Caple, 2008; Ashley-Smith, 2016).

2.5 Machine Learning Algorithms

This study develops machine learning-based methods for microclimate monitoring and prediction at cultural heritage sites, using the supervised learning concept. This involves training a regressor to assign labels to specific data points or regions in the dataset, enabling it to identify hidden patterns and signatures of various labelled factors and make accurate predictions. To ensure effective monitoring and prediction using a variety of data sources, it is crucial to use classifiers that can manage large-scale data and achieve high accuracy quickly. The study focuses on two regressor, XGBoost and Random Forest, which are both capable of achieving these requirements.

2.5.1 Random Forest

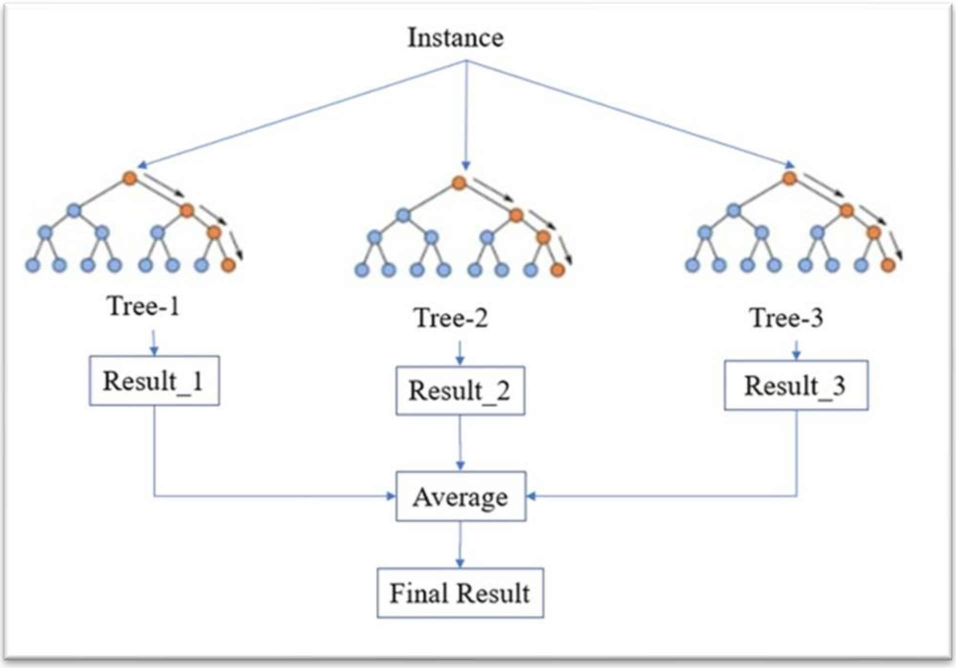

Figure 1: Random Forest Model Architecture

Breiman's Random Forest algorithm, introduced in 2001, is a widely used ensemble learning model that is known for its versatility in performing various tasks such as classification, regression, clustering, interaction detection, and variable selection (Rahmati et al., 2017; Belgiu and Drăguţ, 2016). This learning method leverages the aggregation of decision trees, which divide input data based on specific parameters in a tree-like structure (Ma and Cheng, 2016; Breiman, 2001) (see Fig. 1). Unlike other learning methods, Random Forest is designed to manage complex datasets with high dimensionality, noisy, and missing data, making it particularly useful for microclimate monitoring and prediction at cultural heritage sites.

Each decision tree in a Random Forest model is built using a bootstrapped sample of the data, with nodes split according to the optimal subset and randomly selected predictors at each stage (Araki et al., 2018; Rahmati et al., 2017). The final classification is based on the majority vote of the decision trees, and output is generated accordingly (Micheletti et al., 2014; Rahmati et al., 2017). This approach helps prevent overfitting, where a model learns the training data too well and fails to generalize well to new data. Random Forest's robustness and high-performance capabilities have made it a popular choice in various fields, including image analysis, remote sensing, and ecology.

Furthermore, Random Forest is a highly flexible model that can manage a wide range of input variables, including categorical and continuous variables, and can deal with missing data points by imputing values. The algorithm can also determine the importance of each input variable in predicting the output, enabling researchers to identify the most influential parameters for microclimate monitoring and prediction at cultural heritage sites. Additionally, researchers have developed various extensions and modifications to improve the algorithm's efficiency, such as parallel computing, pruning techniques, and feature importance measures (Balogun et al., 2021; Tella et al., 2021).

One notable feature of Random Forest is its ability to manage interactions between variables, which is important in predicting microclimate parameters at cultural heritage sites. The algorithm can identify and model complex interactions between multiple variables, allowing researchers to better understand the relationships between environmental factors and microclimate patterns. This feature is particularly valuable in cultural heritage sites, where environmental conditions can vary significantly and interactions between environmental factors can be complex.

In conclusion, Random Forest is a powerful machine learning algorithm that has proven to be a valuable tool for microclimate monitoring and prediction at cultural heritage sites. Its robustness, flexibility, and high-performance capabilities make it an attractive choice for managing complex datasets with high dimensionality, noisy, and missing data. Moreover, the algorithm's ability to identify and model interactions between variables provides researchers with valuable insights into the complex relationships between environmental factors and microclimate patterns.

2.5.2 XGBoost

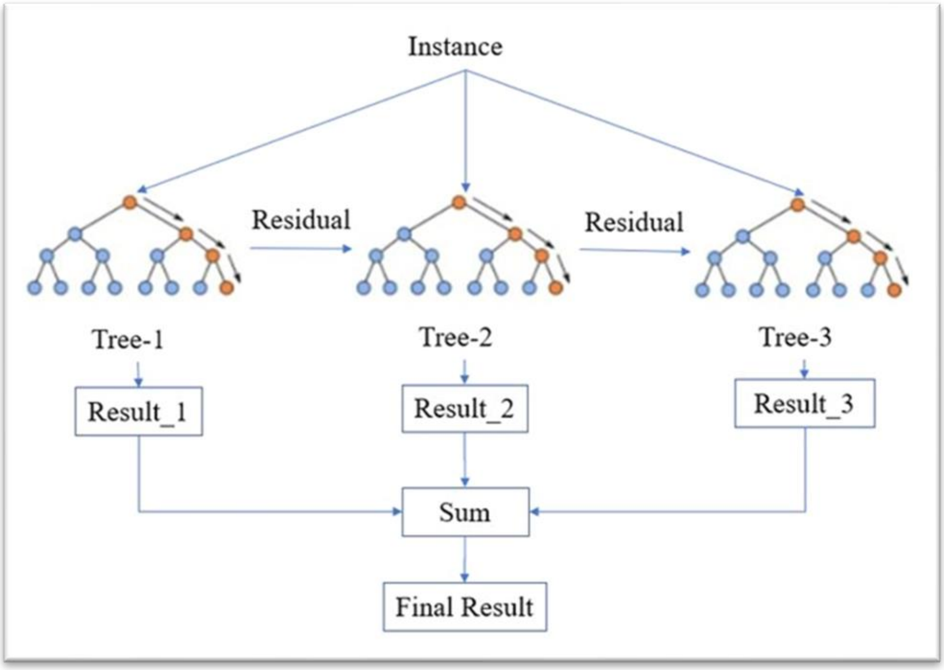

Figure 2: XGBoost Model Architecture

XGBoost is a popular machine learning algorithm that is commonly used for classification tasks. It belongs to the family of boosting algorithms, where multiple weak learners are combined to create a strong model. The algorithm works by iteratively adding decision trees to the model and adjusting their weights based on the error rate of the previous trees. The result is a highly accurate classifier that can manage large and complex datasets.

One of the key advantages of XGBoost is its ability to manage missing data effectively. The algorithm can use surrogate splits to compensate for missing data points, resulting in improved accuracy and robustness in the presence of missing data. XGBoost is also highly optimized for parallel computing, enabling it to process large volumes of data quickly and efficiently.

XGBoost has demonstrated high performance and accuracy when dealing with large-scale, multi-class data in various fields, including remote sensing, medical diagnosis, and natural language processing. Studies have shown that XGBoost can outperform other popular classification algorithms, such as Random Forest and

Support Vector Machines (SVM), in terms of accuracy and efficiency (Bhagwat & Shankar, 2019; Zamani Joharestani et al., 2019; Rumora et al., 2020). This makes it an attractive choice for microclimate monitoring and prediction at cultural heritage sites, where large datasets and high-dimensional feature spaces are common.

XGBoost is highly scalable, which makes it an ideal choice for managing large volumes of satellite data. This enables researchers to perform microclimate monitoring and prediction in real-time, providing valuable insights into the environmental conditions at cultural heritage sites. Additionally, XGBoost is highly optimized for feature selection, allowing researchers to identify the most influential variables for microclimate monitoring and prediction.

In conclusion, XGBoost is a powerful machine learning algorithm that offers several unique advantages for microclimate monitoring and prediction at cultural heritage sites. Its ability to manage missing data, parallel computing, scalability, and feature selection capabilities make it an attractive choice for researchers and practitioners in this field. By leveraging XGBoost's powerful capabilities, researchers can gain valuable insights into the environmental conditions at cultural heritage sites, enabling them to develop more effective strategies for managing and preserving these invaluable assets for future generations.

2.6 Comparative Analysis of Previous Case Studies and the Uses of Machine Learning in Cultural Heritage Preservation

Several studies in the cultural heritage field apply machine learning (ML) techniques for tasks such as automatic text recognition, image annotation, and user preference recommendations. However, the use of ML in conservation science and heritage preservation studies is limited. These studies primarily focus on identifying and classifying materials or structures or using ML to monitor cultural heritage collections or sites for abnormalities. For instance, Zou et al. employed deep learning on image data to locate missing or damaged heritage components in historical buildings, while Kejser et al. used ML to classify the acidity of historic paper samples. Pei et al. utilized machine learning to predict household mite infestation based on indoor climate conditions and found that the extreme gradient boosting (XGBoost) model was the most suitable approach.

Table 1: Comparative Analysis of Previous Case Studies and the Uses of Machine Learning in Cultural Heritage Preservation

Case Study	**Method Used**	**Target Site/Subject**	**Main Outcomes**
Yu et al. (2022)	Convolutional Neural Network Deep Learning	Dunhuang Mogao Grottoes, China	Detected wall painting deterioration; informed preventive measures
(Kumar et al. (2019)	Logistic Regression, Support Vector Machine	Damaged Heritage Sites from 2015 Nepal Earthquake	Classify heritage and not-heritage sites; damage or no damage
Prieto et al., (2017)	Multiple Linear Regression, Fuzzy Logic Models	100 parish churches, located in Seville, Spain	Identifies relevant variables for the functional degradation of the churches.
Gonthier et al., (2019)	Support Vector Machines	Child Jesus, the crucifixion of Jesus, Saint Sebastian	Recognition of iconographic elements in artworks.
Valero et al., (2019)	Logistic Regression, Multi Class Classification	Chapel Royal in Stirling Castle, Scotland	Identifies loss of material defects and discoloration on the walls.

2.7 Implementation of Random Forest and XGboost in Microclimate Monitoring and Prediction

Researchers have been exploring the performance of XGBoost and Random Forest regressor algorithms for microclimate monitoring and prediction in numerous studies. These algorithms have proven to be effective in providing valuable insights for monitoring and managing microclimate factors in different environments.

In a study by J. Angelin Jebamalar & A. Sasi Kumar (2019), a hybrid light tree and light gradient boosting model were used for predicting PM2.5 levels. The proposed method captured PM2.5 data using a sensor with Raspberry Pi and stored it in the cloud, where the hybrid model was used for prediction. The hybrid model outperformed other algorithms, including Linear Regression, Lasso Regression, Support Vector Regression, Neural Network, Random Forest, Decision Tree, and XGBoost. Despite its advantages in handling substantial amounts of data and requiring less space, the hybrid model's limitation was its time-consuming nature.

In a study by Maryam Aljanabi (2020), the authors compared Multilayer Perceptron, XGBoost, Support Vector Regression, and Decision Tree Regressor to predict ozone levels based on temperature, humidity, wind speed, and wind direction. After pre-processing the data and performing feature selection, XGBoost emerged as the superior model for predicting ozone levels on a day-to-day basis.

Soubhik et al. (2018) compared various algorithms, including Linear Regression, Neural Network Regression, Lasso Regression, ElasticNet Regression, Decision Forest, Extra Trees, Boosted Decision Tree, XGBoost, K-Nearest Neighbor, and Ridge Regression, to predict air pollutant levels. They found that XGBoost provided better accuracy due to the arrangement of features in decreasing order of importance for predicting upcoming values. Haotian Jing & Yingchun Wang (2020) used XGBoost to predict the air quality index. By employing weak classifiers and using the shortcomings of previous weak classifiers to form a strong classifier, XGBoost reduced the error between predicted and actual values. However, it was susceptible to outliers and unwanted air pollutants, as it took the previous value into account.

Mejía et al. (2018) determined PM10 levels best with Random Forest but found that it did not accurately predict the levels of dangerous pollutants. However, Random Forest had the advantage of working with incomplete datasets. Pasupuleti et al. (2020) compared Decision Tree, Linear Regression, and Random Forest for predicting air pollutant levels using meteorological conditions and data from the Arduino platform. Random Forest provided more accurate results due to reduced overfitting and error. However, it required more memory and incurred higher costs.

In summary, XGBoost and Random Forest have been applied in various case studies for microclimate monitoring and prediction, with both algorithms demonstrating their effectiveness in predicting air pollutant levels. While they have their respective limitations, these advanced techniques offer valuable tools for researchers and practitioners seeking to understand and manage the air quality in different environments.

2.7.1 Comparison Between Random Forest and XGBoost Algorithms

Table 2: List of Difference between Random Forest and XGBoost Algorithms

Criteria	XGBoost	Random Forest
Model Type	Gradient boosting decision tree ensemble (Chen & Guestrin, 2016)	Decision tree ensemble (Breiman, 2001)
Learning Approach	Gradient boosting, optimizing loss function (Friedman, 2001)	Bagging, independent decision trees combined through majority voting or averaging (Liaw & Wiener, 2002)

Managing Missing Data	Imputation or treating missing values as separate categories (Chen & Guestrin, 2016)	Imputation or treating missing values as separate categories (Breiman, 2001)
Overfitting Prevention	Shrinkage and regularization (Chen & Guestrin, 2016)	Averaging results of multiple decision trees (Breiman, 2001)
Interpretability	Can provide feature importance information	Easier to interpret due to simpler decision tree structure (Breiman, 2001)
Speed and Scalability	Slower in training due to sequential nature (Chen & Guestrin, 2016)	Faster and more parallelizable due to independent tree construction (Breiman, 2001)
Performance	Compare using MAE, RMSE, R-squared (Caruana & Niculescu-Mizil, 2006)	Compare using MAE, RMSE, R-squared (Caruana & Niculescu-Mizil, 2006)
Feature Importance	Can rank input variables by importance (Chen & Guestrin, 2016)	Can rank input variables by importance (Breiman, 2001)
Hyperparameter Tuning	Requires tuning, may be more sensitive to hyperparameter settings (Probst, Wright, & Boulesteix, 2019)	Requires tuning, may be less sensitive to hyperparameter settings (Probst, Wright, & Boulesteix, 2019)
Memory Usage	Less memory usage due to sequential nature (Chen & Guestrin, 2016)	More memory usage due to storage of multiple decision trees (Breiman, 2001)

2.8 Chapter Summary

Through this chapter, the study focuses on the preservation of cultural heritage sites through machine learning-based microclimate monitoring, with a specific focus on the application of Random Forest and XGBoost algorithms at two heritage sites in Johor Bahru and Melaka. The review begins with an overview of the impact of climate change on cultural heritage sites and the importance of their preservation. It then explores the impact of microclimate factors on cultural heritage sites, including temperature, rainfall, humidity, and wind speed, and the traditional reactive methods used for preservation. The limitations of reactive maintenance and the need for a shift towards proactive and preventive measures are discussed, such as regular monitoring and preventive conservation. Finally, the review explains the use of machine learning algorithms in microclimate monitoring and prediction, specifically Random Forest and XGBoost, and their application in this study. The review highlights the significance of using machine learning-based approaches for preserving cultural heritage sites and the potential benefits of incorporating them into preservation strategies.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This chapter will elaborate more on the methodology used in this research which includes the research design framework, steps and techniques used for the research. The overall research workflow consists of four phases which will be discussed further in this chapter. Each step of the framework will be elaborated in detail on how it will be implemented to this research including the techniques that will be used.

3.2 Research Workflow

The research methodology framework has four main phases which are Literature Review, Problem Definition, Experiment & Evaluation and Result Documentation. The framework starts with Phase 1 which is the literature review of the study, it related to the process of gathering information related to microclimate monitoring and prediction and machine learning techniques as shown in Figure 3.1. The framework then continues with the second phase which is the problem definition phase of the thesis, the problem on microclimate monitoring & prediction. The next phase is the experiment and evaluation phase which is how to conduct the research and how to evaluate data of the results acquired. The last phase is the result documentation phase where end results will be reported.

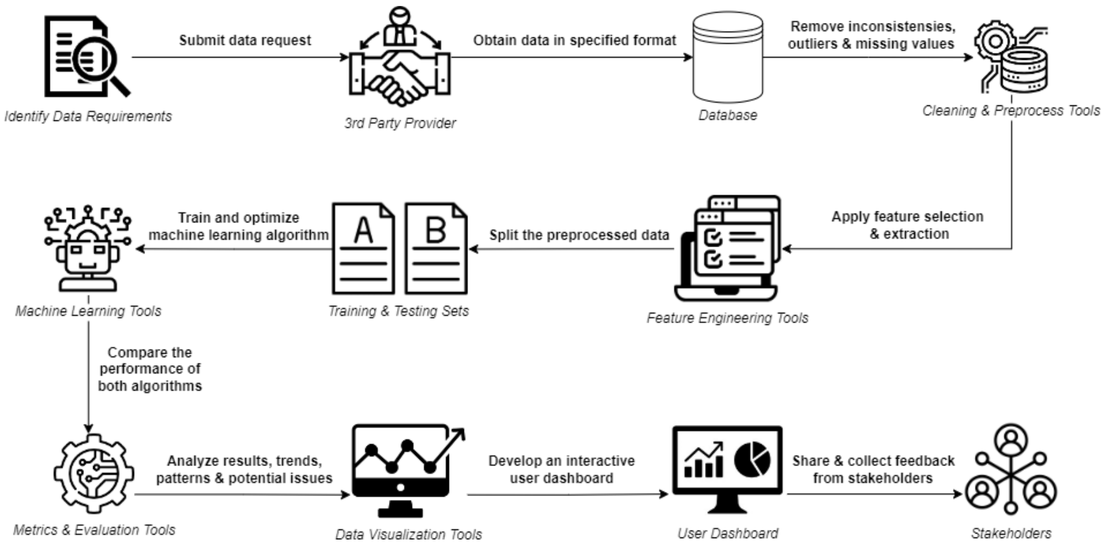

Figure 3: Research Workflow

3.2.1 Phase 1: Literature Review

In the first phase, a comprehensive literature review is conducted to gather relevant information on preserving cultural heritage sites through microclimate monitoring and prediction using Random Forest and XGBoost algorithms. Various scholarly sources, including journals, articles, and theses, are explored to understand the current state of research in this field. The literature review delves into topics such as data collection methods, pre-processing techniques, and the application of machine learning models. By examining existing studies, this phase helps identify gaps, challenges, and potential solutions for effectively monitoring and predicting microclimate conditions at heritage sites. The insights gained from the literature review form the foundation for the subsequent phases and guide the research towards developing a robust methodology.

3.2.2 Phase 2: Data Collection and Preprocessing

In the second phase, the focus shifts to obtaining microclimate data from the Copernicus Climate Change Service (C3S) for a specific heritage site in Johor Bahru. This data, encompassing temperature, relative humidity, precipitation, and wind speed measurements, serves as the basis for subsequent analysis and modelling. To ensure data quality, a rigorous pre-processing stage is undertaken, which involves cleaning the raw data and addressing any missing values or outliers. Techniques such as interpolation, statistical analysis, and data imputation are employed to enhance the integrity and accuracy of the collected data. Additionally, feature engineering techniques are applied to extract meaningful features from the raw data, enabling the capturing of temporal dependencies and relationships between variables. This phase prepares the dataset for further analysis and model development in the subsequent phases.

3.2.3 Phase 3: Machine Learning Model Development

The third phase revolves around the development of machine learning models for microclimate monitoring and prediction. The pre-processed data is divided into training and testing sets, with the training set used to train and optimize the Random Forest and XGBoost algorithms. Various parameters and hyperparameters are fine-tuned using techniques like grid search and cross-validation to achieve optimal model performance. The trained models are then evaluated using appropriate assessment metrics, such as mean absolute error and mean squared error, to assess their predictive capabilities. This evaluation process helps determine the effectiveness and performance of the Random Forest and XGBoost algorithms in accurately predicting microclimate patterns for the designated heritage site. The models' performance and generalizability are crucial factors in ensuring the reliability and usefulness of the developed models for microclimate monitoring and prediction.

3.2.4 Phase 4: Dashboard Development

In the fourth phase, a user-friendly dashboard is designed and developed to visualize and present the microclimate data in a comprehensible manner. The dashboard provides real-time insights into the microclimate conditions of the heritage site, displaying key metrics such as temperature, humidity, and wind speed. The trained machine learning models are integrated into the dashboard to provide recommendations for preventive maintenance actions based on the analysed data. Additionally, visualization tools and interactive features are incorporated to facilitate a better understanding of trends and patterns in the microclimate data. The dashboard serves as a valuable tool for local authorities and stakeholders involved in the preservation of cultural heritage sites, enabling them to make informed decisions and take proactive measures to mitigate potential issues that may impact the site's condition.

3.3 Justification of Tools, Techniques and Data

The chosen tools for this research include data collection from the Copernicus Climate Change Service (C3S), data pre-processing techniques, machine learning algorithms (Random Forest and XGBoost), and dashboard development. These tools have been selected based on their suitability for addressing the research objectives and providing valuable insights for preventive maintenance strategies at the designated heritage site in Johor Bahru.

Microclimate data from Copernicus is essential for understanding the environmental conditions at the heritage site. Temperature, precipitation, humidity, wind speed are crucial parameters that can affect the preservation of heritage structures. By obtaining this data, we can assess the impact of these environmental factors on the site's structural integrity and identify potential maintenance issues.

The research utilizes machine learning techniques to analyse the collected microclimate data and develop predictive models for preventive maintenance. Random Forest and XGBoost algorithms are chosen due to their proven effectiveness in handling complex relationships between variables and handling both regression and classification tasks. These algorithms can capture temporal dependencies in the data and provide accurate predictions for future microclimate conditions.

The preservation of heritage sites is of paramount importance to maintain cultural identity and historical significance. By utilizing advanced data analysis techniques, this research aims to provide insights into the impact of microclimate conditions on the designated heritage site in Johor Bahru. The findings can help authorities develop targeted preventive maintenance strategies to ensure the site's long-term preservation.

By collecting and analysing microclimate data, this research enables data-driven decision making for preventive maintenance. Traditional approaches may not consider the dynamic nature of microclimate conditions and their impact on heritage sites. The use of machine learning algorithms allows for a more comprehensive understanding of the relationships between environmental factors and potential maintenance issues, leading to more informed decision making.

Implementing preventive maintenance strategies based on predictive models can result in cost savings and increased efficiency. By identifying trends, patterns, and potential issues, maintenance activities can be prioritized, scheduled, and targeted accordingly. This approach minimizes reactive maintenance efforts, reduces costs associated with emergency repairs, and optimizes resource allocation.

The development of a user-friendly dashboard integrating real-time microclimate data and machine learning models provides a powerful tool for monitoring and maintenance planning. The visualization tools within the dashboard help users understand trends and patterns in the data, facilitating proactive decision making. This allows local authorities to respond promptly to changing microclimate conditions and potential threats to the heritage site.

The research encourages collaboration between local authorities, heritage site management teams, and relevant stakeholders. By involving these parties in the evaluation and testing phases, their feedback can be gathered to refine the system and ensure its usability and effectiveness. Engaging stakeholders throughout the research process increases their ownership and facilitates the adoption of preventive maintenance strategies.

3.4 Chapter Summary

This chapter summarized the four phases of the research study. The literature review phase involved a comprehensive review of relevant literature, providing a solid knowledge base for the subsequent phases. The data collection and pre-processing phase focused on obtaining and cleaning microclimate data, while the machine learning model development phase involved training and evaluating Random Forest and XGBoost algorithms. The final phase focused on developing a user-friendly dashboard that visualizes the microclimate data and provides maintenance recommendations.

CHAPTER 4

RESEARCH DESIGN AND IMPLEMENTATION

4.1 Introduction

This chapter discusses in depth the research design and implementation of the research methodology described in the previous chapter. The proposed solution will be broken down into several steps, including the data collection, pre-processing, feature extraction, training and testing and machine learning models development.

4.2 Proposed Solution

The proposed solution encompasses several steps to address the objectives outlined in the research scope. Initially, microclimate data will be acquired from the Copernicus Climate Change Service (C3S), focusing on parameters like temperature, humidity, precipitation, and wind speed. Subsequently, the collected data will undergo preprocessing to ensure quality and reliability, including handling missing values and outliers. Relevant features will be selected for model training, emphasizing factors such as temperature variations, humidity levels, and wind patterns. Two machine learning algorithms, Random Forest and XGBoost, will be implemented and compared for their performance in microclimate monitoring and prediction. Additionally, a dashboard will be designed and developed using data visualization tools like Matplotlib to display real-time microclimate data. Finally, the effectiveness of the developed algorithms and dashboard will be evaluated based on their ability to assist local authorities in planning preventive maintenance actions for the heritage site, considering metrics such as prediction accuracy and user feedback. Through these steps, the proposed solution aims to provide a comprehensive framework for enhancing microclimate monitoring and management for the preservation of the Johor Bahru High Court, Sultan Ibrahim Building, Sultan Abu Bakar Mosque and Malayan Railway Museum.

4.3 Flow of Overall Data Processing

In this section, we outline the process of downloading, extracting, and processing microclimate data from the Copernicus database and subsequently generating various analyses and visualizations.

To begin, we downloaded the dataset covering the period from 1940 to 2023 for each microclimate from the Copernicus Climate Data Store. The data was acquired in NetCDF format, which is a standard format for storing multidimensional scientific data. To convert the NetCDF files into a more usable format, we used a Python script, referred to as Script 20. This script extracts the data into .dat files, for instance, Extract-194001.dat for the January 1940 Rain dataset. Each .dat file consists of three columns: latitude, longitude, and the Rain data. The script outputs all the latitude and longitude coordinates along with the corresponding rain data for each observed area.

Next, we used the .dat files generated by Script 20 as input for Script 54. Script 54 processes these files to plot the monthly data, specifically creating Heatmaps of Monthly Accumulated Rainfall for each month of the desired year. Following this, we employed Script 60 to extract data for specific latitude and longitude coordinates, such as those for Sultan Ibrahim Building and A Famosa. Script 60 identifies the nearest available latitude and longitude in the dataset to the chosen coordinates. For example, when selecting the coordinates for Sultan Ibrahim Building, the output file will include columns for the year and month, the chosen latitude and longitude, the nearest latitude and longitude from the data, and the corresponding rain data. Each month's data is saved in separate files, and data for different years is organized into distinct folders.

We then used Script 80 to merge the datasets from various files into a comprehensive dataset, facilitating further analysis. Finally, with the merged dataset from Script 80, we ran Script 100 to generate histograms depicting the monthly average rainfall trends over the selected period. This visualization allows for an easy comparison of rainfall patterns across different months and years.

The Plotting script performs a comprehensive analysis of climate data for Melaka and Johor Bahru, focusing on temperature, wind speed, relative humidity, and rainfall. It begins by loading the respective datasets from CSV files from the merged datasets in script 80 and reshaping them from a wide format to a long format to facilitate easier plotting and analysis. The data is then merged into a single dataset, allowing for a holistic view of the climate variables. Various scatter plots are created to explore the relationships between the different climate variables, and a correlation matrix is generated to visualize the strength of these relationships. The script also produces anomaly plots for each climate variable, highlighting deviations over time. Additionally, it generates trend lines to illustrate the average monthly values for each variable, providing insights into their general behavior throughout the year. Finally, the merged dataset is saved to a CSV file for further analysis.

Next, the prediction script utilizes machine learning models to predict climate data for Melaka in 2024. It starts by loading datasets for rainfall, temperature, humidity, and wind speed. The core functionality is encapsulated in the train_and_predict function, which separates the data into features and target variables, excluding the year 2024. It then trains two models, Random Forest and XGBoost, for each month using data from all other years. Predictions for 2024 are generated for each month by these models. The script prints the predicted values and visualizes them using bar plots, comparing the outputs of the Random Forest and XGBoost models. This process is repeated for each type of climate data, providing monthly predictions for rainfall in millimeters, temperature in degrees Celsius, relative humidity in percentage, and wind speed in meters per second.

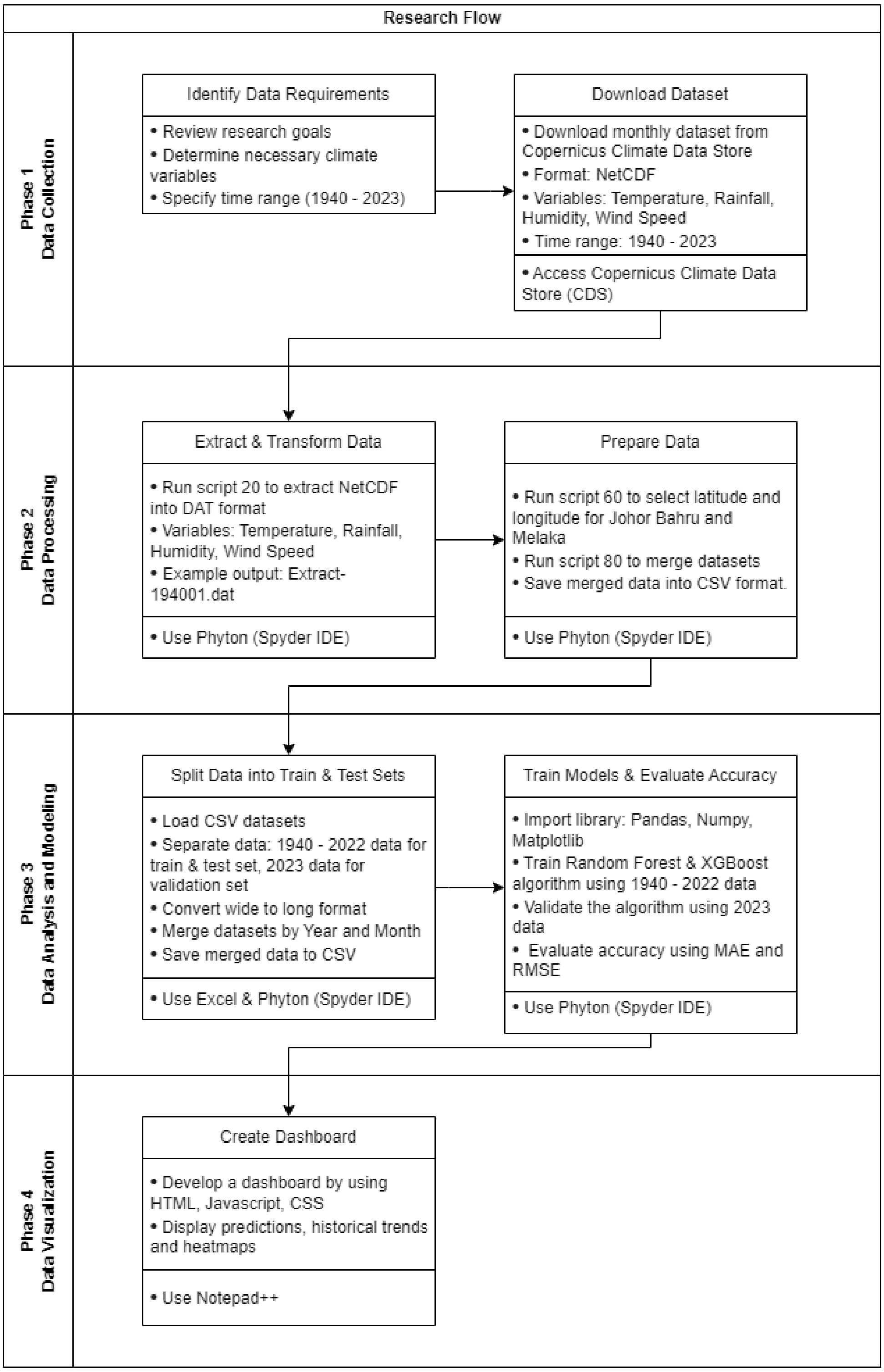

Figure 4: Research Flow

4.4 Research Area Zone Mapping

In the context of this research, a research area zone mapping was established to focus on the preservation of cultural heritage sites in Johor Bahru and Bandar Hilir, Melaka. The selected heritage sites for this study are:

Heritage Sites	Description
Sultan Ibrahim Building	This building holds historical and architectural significance as the state secretariat building of Johor. It represents the rich cultural heritage of the region.
A Famosa	A Famosa was a Portuguese fortress built in Malacca, the oldest part of the fortress was a five-storey keep which eventually gave its name to the fortress as a whole.

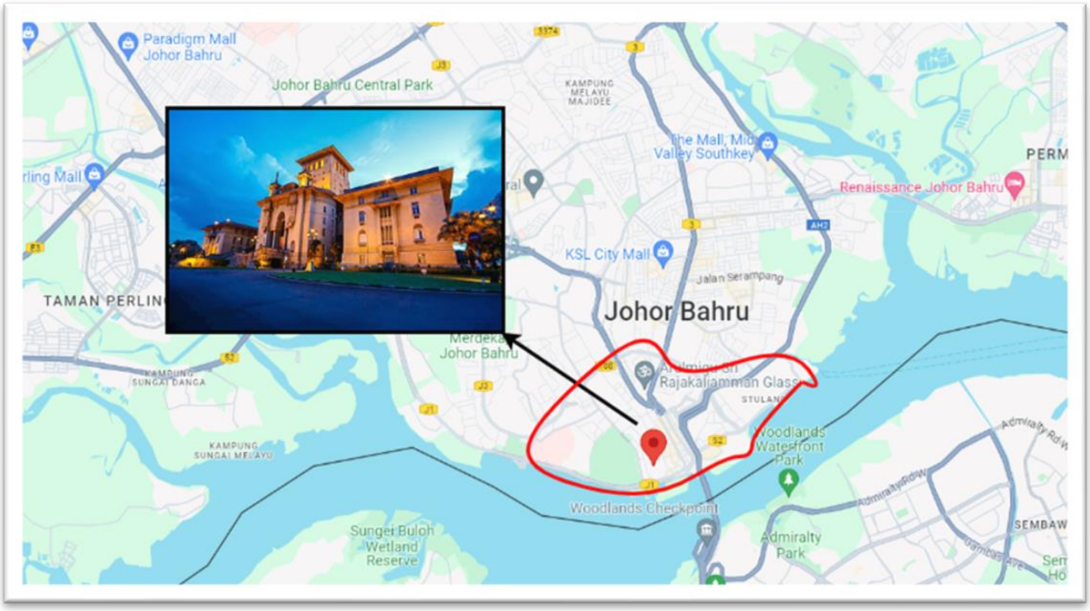

Figure 5: Sultan Ibrahim Building, Johor Bahru

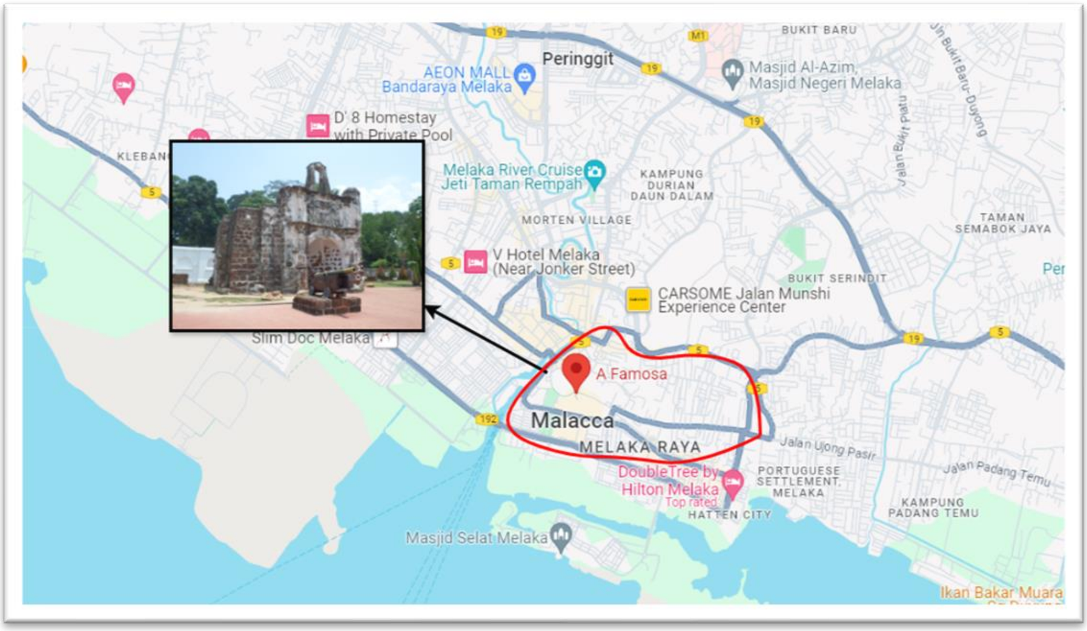

Figure 6: A Famosa, Bandar Hilir, Melaka

4.5 Experiment Design

4.5.1 Microclimate Data Collection Process

In this research study, the microclimate data was obtained from the ECMWF Reanalysis v5 (ERA5) dataset, provided by the Copernicus Climate Change Service (C3S) at the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5 is the fifth generation of ECMWF's atmospheric reanalysis, offering a comprehensive global climate analysis spanning from January 1940 to the present day.

The data was available in the NetCDF format, a widely used self-describing, machine-independent data format for array-oriented scientific data. To extract and process the data, we utilized Spyder, a powerful Integrated Development Environment (IDE) for Python, which facilitated efficient data handling and analysis.

For this research, we collected microclimate data spanning a substantial time range, from 1940 to 2023. This extended historical period allowed us to gather a significant amount of data, enabling more reliable and robust predictions related to the microclimate conditions at the designated heritage site.

Historical data plays a crucial role in understanding and predicting microclimate patterns in the context of heritage sites. By analyzing long-term data trends, we can gain valuable insights into the site's microclimate dynamics, including temperature, humidity, wind patterns, and precipitation levels. These insights are essential for developing effective strategies to preserve and protect the heritage site from potential environmental impacts.

4.5.2 Data Collection

The data was collected from the Climate Data Store (CDS) Copernicus website. The chosen dataset for this research is ERA5 monthly averaged data on single levels from 1940 to present. Single level is chosen because the CDS mentioned that dataset on single level is better for forecasting rather than dataset on pressure level. So for each rainfall, humidity, temperature and wind speed, we downloaded the monthly data from 1940 to 2023 at the specified time (00:00 UTC). and covers a defined geographical area. The data is requested in NetCDF format, which is a common format for storing multidimensional scientific data. The geographical area of interest is specified by the latitude and longitude coordinates [10, 90, -10, 130], representing the region from 10°S to 90°N latitude and from 130°E to 10°W longitude. The retrieved data is then stored in a NetCDF file (e.g., Monthly-Precip-Jan-1940-2024.nc) for further analysis and visualization.

The process followed by processing and extracting the the raw data files as shown in Figure 8. The script loops through a list of month names (e.g., 'Jan', 'Feb', 'Mar', etc.) and opens each corresponding NetCDF file containing temperature data for that month. It reads the latitude, longitude, and temperature variables from the file, as well as the time dimension and its associated units. For each file, the script converts the time values from the NetCDF file to Python datetime objects using the num2date function from the NetCDF4 library. It then prints the available time observations, allowing the user to select a specific time index for further processing.

After selecting a time index, the script extracts the corresponding temperature data and converts it from Kelvin to Celsius. It then creates a grid of latitude and longitude values using np.meshgrid and combines the temperature data with the grid coordinates into a single 2D array. The script then creates a folder structure based on the year and saves the extracted temperature data, along with the corresponding latitude and longitude coordinates, into a text file named Extract-YYYYMM.dat. The file is saved in a subdirectory named after the year, within a directory called '20-Ekstrak' located in the current working directory. Overall, this script is designed to extract and process temperature data from a set of NetCDF files, convert the data to a more accessible format which is DAT files format. This process can be useful for further analysis, visualization, or integration with other data sources.

```
data_raw='../Data-RAW-RAIN/'

# files_month=['Jun']
files_month=['Jan','Feb','Mac','Apr','May','Jun','Jul','Aug','Sep','Oct','Nov'

for m in files_month:
    filename='Monthly-Precip-'+m+'-1940-2023.nc'
    f=nc.Dataset(data_raw+filename)
    v=f.variables; keys=f.variables.keys(); data={}

    for i in keys:
        data[i]=np.squeeze(v[i][:])
        print(i)

    lat=data['latitude']
    lon=data['longitude']
    rain=data['tp'][:]

    times = f.variables['time'][:]
    units=f.variables['time'].units
    ptime = num2date (times[:], units, calendar='gregorian')
    print ('Available Time Observation to Plot : (index,pressure) ')
```

Figure 7: Data Extraction and Processing

10.000	90.000	26.499
10.000	90.250	26.789
10.000	90.500	26.062
10.000	90.750	24.172
10.000	91.000	21.628
10.000	91.250	19.883
10.000	91.500	18.938
10.000	91.750	17.920
10.000	92.000	18.684
10.000	92.250	17.811
10.000	92.500	17.157
10.000	92.750	16.030
10.000	93.000	14.976
10.000	93.250	13.958

Figure 8: Processed Dataset in DAT file format (latitude, longitude, values)

The script in Figure 9 is designed to visualize monthly average temperature data for a specific region, with Malaysia as an example. It starts by importing necessary libraries for data processing and plotting. After setting up the directory structure, it reads temperature data files, processes them to extract latitude, longitude, and temperature values, and creates a contour plot of the temperature data on a map. The map is centred on the region of interest which in this case, Malaysia and includes country and state boundaries, coastlines, parallels, and meridians for reference as shown in Figure 5 below.

```
# Define colormap and contour levels
cmap = cm.s3pcpn_l
clevprecip = np.arange(0, 1200, 50)
norm1 = mpl.colors.BoundaryNorm(clevprecip, cmap.N)

# Create the contour plot
cf = m.contourf(X, Y, Z, clevprecip, cmap=cmap, norm=norm1, latlon=True)
cbar = m.colorbar(cf, location='bottom', pad="12%")
cbar.ax.tick_params(labelsize=10)
cbar.set_label('Monthly Accumulated Rainfall (mm/month)', fontsize=10)

# Add title to the plot
title1 = 'ERA5- Monthly Accumulated Rainfall for ' + nama_file
plt.title(title1)

# Save the plot as a PNG file
plt.savefig(path3 + nama_file + '.png', dpi=500, bbox_inches='tight')
```

Figure 9: Plotting Monthly Average Temperature Data

Additionally, it overlays administrative boundaries of Malaysian states obtained from a shapefile. The script utilizes a colormap to represent temperature variations and adds a colorbar for reference. Finally, it saves the generated plot images, each corresponding to a specific data file, for further analysis or visualization. Overall, this script facilitates the visualization of monthly temperature patterns for a chosen region, aiding in understanding climate variations over time.

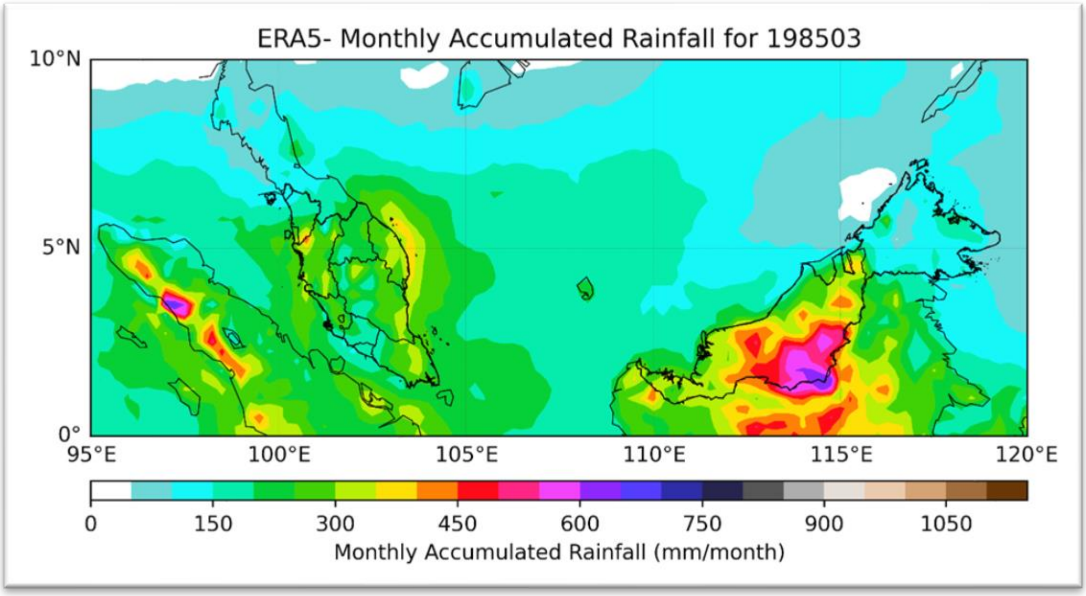

Figure 10: Monthly Accumulated Rainfall Sample Output

The script described in Figure 11 is designed to extract location-specific meteorological data from a collection of data files. It allows users to specify one or more locations of interest, along with optional criteria such as specific years or a range of years. After importing necessary libraries, the script prompts users to input the location(s) they are interested in, along with any desired years. It then creates directories for storing both the original data files and the extracted location-specific data.

For each combination of year and location, the script searches for matching data files and reads the data, typically containing latitude, longitude, and meteorological parameters like temperature or rainfall rates. It calculates the distance between each data point and the specified location to find the closest data point, from which it extracts relevant values. The extracted location-specific data is then saved to new files, named to indicate the location, year, and time period. This process streamlines the extraction of meteorological data tailored to specific locations, eliminating the need for manual data searching and filtering. This functionality is valuable for researchers, meteorologists, or anyone interested in analysing weather patterns or environmental conditions at specific locations.

```
# Extract latitude, longitude, and rainfall rate
lat = data[:, 0]
lon = data[:, 1]
rain_rate = data[:, 2]

# Define the target latitude and longitude (location to select data for)
in_lats1 = [q]
in_lons1 = [r]

# Find the closest data point to the target location
ind = []
for i in range(1):
    dist = (lat - in_lats1[i])**2 + (lon - in_lons1[i])**2
    ind.append(np.where(dist == np.min(dist))[0][0])

    lat2 = lat[ind]
    lon2 = lon[ind]
    rain_rate2 = rain_rate[ind]

# Combine the date, target location, and selected data into an array
data3 = [np.array([dates]), in_lats1, in_lons1, lat2, lon2, rain_rate2]
data3 = np.transpose(data3)
```

Figure 11: Extracting Location-Specific Data from Data Files

The script described in Figure 7 is designed to merge and consolidate location-specific microclimate data from multiple files into a single file for each location of interest. This consolidation process helps in organizing and simplifying the data for easier analysis or visualization. After importing necessary libraries and defining the locations and years of interest, the script creates directories for storing both the extracted location-specific data files and the merged data files.

For each combination of year and location, the script reads the monthly data files containing information such as date, latitude, longitude, and meteorological parameters like temperature or rainfall rates. It then extracts the relevant temperature or rainfall rate values for each month and organizes them into a list, along with the corresponding year. These lists are then appended to a larger list, accumulating the data for all years and locations. Once all specified years and locations have been processed, the accumulated data list is saved to a new file in the '80-Merge-Data' directory. This file contains the merged and consolidated data for the specific location, with each row representing a year and the corresponding temperature or rainfall rate values for each month.

```python
# Load the data for each month of the year
data1 = np.loadtxt(path3 + 'Data-Location-' + year + '01' + '.dat', dtype='float')
data2 = np.loadtxt(path3 + 'Data-Location-' + year + '02' + '.dat', dtype='float')
data3 = np.loadtxt(path3 + 'Data-Location-' + year + '03' + '.dat', dtype='float')
data4 = np.loadtxt(path3 + 'Data-Location-' + year + '04' + '.dat', dtype='float')
data5 = np.loadtxt(path3 + 'Data-Location-' + year + '05' + '.dat', dtype='float')
data6 = np.loadtxt(path3 + 'Data-Location-' + year + '06' + '.dat', dtype='float')
data7 = np.loadtxt(path3 + 'Data-Location-' + year + '07' + '.dat', dtype='float')
data8 = np.loadtxt(path3 + 'Data-Location-' + year + '08' + '.dat', dtype='float')
data9 = np.loadtxt(path3 + 'Data-Location-' + year + '09' + '.dat', dtype='float')
data10 = np.loadtxt(path3 + 'Data-Location-' + year + '10' + '.dat', dtype='float')
data11 = np.loadtxt(path3 + 'Data-Location-' + year + '11' + '.dat', dtype='float')
data12 = np.loadtxt(path3 + 'Data-Location-' + year + '12' + '.dat', dtype='float')

# Extract rainfall data from each month's data
rain1 = data1[5]
rain2 = data2[5]
rain3 = data3[5]
rain4 = data4[5]
rain5 = data5[5]
rain6 = data6[5]
rain7 = data7[5]
rain8 = data8[5]
rain9 = data9[5]
rain10 = data10[5]
rain11 = data11[5]
rain12 = data12[5]
```

Figure 12: Merging and Consolidating Location-Specific Microclimate Data

By running this script, users can efficiently merge and consolidate location-specific meteorological data from multiple files into a single file for each location of interest. This consolidated data can then be further analysed to identify trends, patterns, or anomalies in the meteorological data over time, or used for creating visualizations or reports.

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2	1940	24.549	25.042	26.119	25.932	26.282	26.482	26.675	26.337	25.94	25.828	25.25	24.782
3	1941	24.982	25.426	25.895	26.328	26.235	26.62	26.15	26.18	25.448	25.553	25.39	25.116
4	1942	24.564	25.072	25.609	25.785	26.501	26.454	25.768	25.865	25.575	25.617	24.99	24.281
5	1943	24.674	25.025	25.299	25.763	26.428	26.838	26.198	25.878	25.512	25.234	25.021	24.619
6	1944	24.499	25.281	25.693	25.856	25.845	26.13	26.082	26.211	25.835	25.918	25.385	25.165
7	1945	24.75	24.888	24.575	25.675	26.159	26.177	25.934	25.729	26.139	25.651	24.93	24.874
8	1946	24.578	24.238	25.653	25.76	26.182	26.382	26.264	26.14	25.96	25.579	25.425	25.128
9	1947	25.069	25.25	25.737	26.157	26.188	26.277	25.837	25.643	25.456	25.6	25.367	24.638
10	1948	24.486	25.178	26.134	26.634	26.367	26.221	26.012	25.999	25.904	25.96	25.224	25.188
11	1949	25.35	25.665	26.729	27.245	27.275	26.793	26.201	25.969	25.78	26.288	25.854	25.336
12	1950	25.803	25.858	26.145	26.334	26.5	26.408	25.953	25.552	26.118	25.862	25.375	25.13
13	1951	24.79	25.221	25.679	26.427	26.419	26.408	25.746	26.243	26.124	26.163	26.233	25.664
14	1952	25.483	25.852	26.28	26.399	26.834	26.506	26.125	26.175	26.116	26.287	25.62	25.329
15	1953	25.184	25.311	25.88	26.542	26.496	26.491	25.781	26.269	25.927	26.012	26.095	25.619
16	1954	25.32	25.376	25.865	26.142	26.323	26.299	25.771	26.012	25.967	25.514	25.268	24.897
17	1955	24.515	25.534	25.858	26.124	26.938	26.585	26.05	25.678	25.692	25.949	26.044	24.779
18	1956	24.589	25.348	25.887	26.361	26.446	26.386	26.106	25.863	25.724	25.429	25.352	24.983
19	1957	24.906	25.485	25.863	26.233	26.265	26.7	26.355	26.282	26.209	25.993	25.791	25.211
20	1958	25.808	25.669	26.322	26.834	27.036	26.993	26.97	26.223	26.481	26.211	25.74	25.484
21	1959	25.218	25.838	25.997	26.354	26.768	26.522	26.429	26.18	26.426	26.233	25.706	25.627
22	1960	25.276	25.376	26.07	26.524	27.058	26.595	26.161	26.454	26.065	26.193	25.903	25.413
23	1961	25.18	25.685	26.466	26.644	27.087	26.525	26.123	26.131	26.145	26.405	25.721	25.214
24	1962	24.946	25.165	25.825	26.338	27.072	26.48	26.469	25.608	26.128	26.214	25.726	25.345
25	1963	24.696	24.651	25.892	26.749	27.03	26.754	26.213	26.22	26.26	25.93	25.847	25.401
26	1964	25.702	25.496	26.054	26.722	27.049	26.449	25.669	26.185	26.135	25.873	25.709	24.398

Data-Merge-Sultan Ibrahim Build

Figure 13: Merged Temperature Data for Sultan Ibrahim Building Area

4.5.3 Splitting of Data into Training and Testing Sets

In the below code snippet, the train_test_split function from scikit-learn is used to split the pre-processed data (X_new) and the corresponding target variable (y) into training and testing sets. The test_size parameter is set to 0.2, indicating that 20% of the data will be used for testing, while the remaining 80% will be used for training. The random_state parameter is set to 42 to ensure reproducibility of the split. Then, it will proceed with training and evaluating machine learning models using the X_train, y_train for training, and X_test, y_test for testing.

```
from sklearn.model_selection import train_test_split

# Split the preprocessed data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_new, y, test_size=0.2, random_state=42)
```

Figure 14: Split the pre-processed data into training and testing sets with an 80-20 ratio

4.5.4 Training and Evaluation of Machine Learning Models

The next step after splitting the data into training and testing sets is to train and evaluate the machine learning models. The figure shows the code for training and evaluating the Random Forest and XGBoost algorithms: In this code snippet, the Random Forest and XGBoost models are initialized and trained using the training data (X_train and y_train). Then, predictions are made on the testing data (X_test) using the trained models. The mean absolute error (MAE) and mean squared error (MSE) are calculated to evaluate the performance of both models.

```
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error

# Initialize and train the Random Forest model
rf_model = RandomForestRegressor()
rf_model.fit(X_train, y_train)

# Make predictions on the testing set using the trained Random Forest model
rf_predictions = rf_model.predict(X_test)

# Calculate evaluation metrics for the Random Forest model
rf_mae = mean_absolute_error(y_test, rf_predictions)
rf_mse = mean_squared_error(y_test, rf_predictions)

# Initialize and train the XGBoost model
xgb_model = XGBRegressor()
xgb_model.fit(X_train, y_train)

# Make predictions on the testing set using the trained XGBoost model
xgb_predictions = xgb_model.predict(X_test)

# Calculate evaluation metrics for the XGBoost model
xgb_mae = mean_absolute_error(y_test, xgb_predictions)
xgb_mse = mean_squared_error(y_test, xgb_predictions)

# Print the evaluation results
print("Random Forest - Mean Absolute Error:", rf_mae)
print("Random Forest - Mean Squared Error:", rf_mse)
print("XGBoost - Mean Absolute Error:", xgb_mae)
print("XGBoost - Mean Squared Error:", xgb_mse)
```

Figure 15: Train and evaluate the Random Forest and XGBoost algorithms

4.6 Parameter and Testing Methods

In order to evaluate the effectiveness of the proposed solution, several parameters are measured during the testing phase. These parameters provide valuable information about the performance and efficacy of the developed models. The parameters to be measured include:

4.6.1 Parameters to be Measured

1. Prediction Accuracy: The accuracy of the predictive models in capturing and predicting the microclimate conditions is measured. This indicates how well the models are able to estimate the actual values of temperature, humidity, wind speed, solar radiation, and rainfall.

2. Mean Absolute Error (MAE): MAE is measured to determine the average absolute difference between the predicted and actual values. It provides insights into the average prediction error across all the microclimate parameters.

3. Mean Squared Error (MSE): MSE is calculated to assess the average squared difference between the predicted and actual values. It measures the overall variance between the predicted and actual values.

4.6.2 Testing Procedure

1. Splitting Data: The pre-processed microclimate data is divided into training and testing sets, typically using an 80:20 split. The training set is used to train the machine learning models, while the testing set is used for evaluating the performance.

2. Model Evaluation: The trained Random Forest and XGBoost models are applied to the testing set to make predictions for the microclimate parameters.

The predicted values are then compared with the actual values from the testing set.

3. Calculation of Evaluation Metrics: The evaluation metrics, such as MAE and RMSE, are calculated based on the predicted and actual values. These metrics provide quantitative measures of the model's performance.

4. Analysis and Interpretation: The evaluation results are analysed to gain insights into the accuracy and effectiveness of the trained models. The performance of the models is assessed based on the evaluation metrics and compared to determine the superior algorithm for microclimate prediction.

4.7 Results and Discussion

The microclimate predictions for Johor Bahru in 2023 using Random Forest and XGBoost algorithms reveal interesting insights into the performance of these models. Both algorithms demonstrated similar prediction patterns, but with some notable differences in their accuracy and reliability.

For humidity predictions, both Random Forest and XGBoost models showed comparable performance. The Random Forest model achieved a Mean Absolute Error (MAE) of 1.30, Root Mean Square Error (RMSE) of 1.51, and an R-squared value of 0.24.

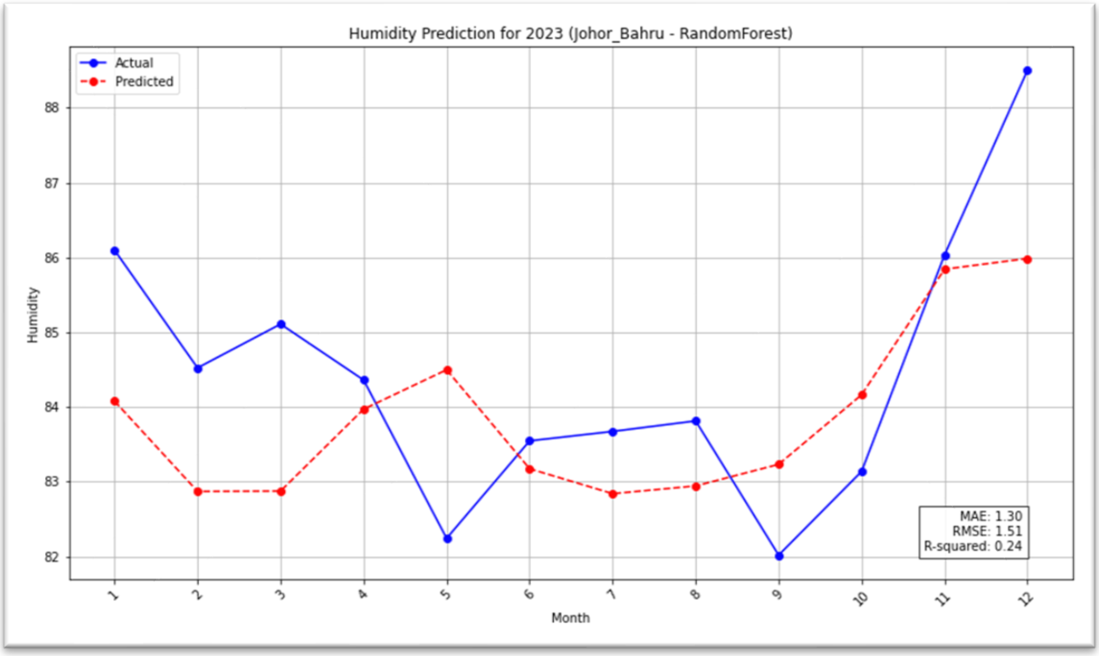

Figure 16: Humidity Prediction for 2023 (Johor Bahru - Random Forest)

The XGBoost model performed slightly better with an MAE of 1.29, RMSE of 1.51, and an R-squared value of 0.25. These results indicate that both models have similar error rates, with XGBoost having a marginally lower MAE and higher R-squared value. The low R-squared values suggest that both models explain only about 24-25% of the variance in humidity, indicating room for improvement in capturing the full complexity of humidity patterns.

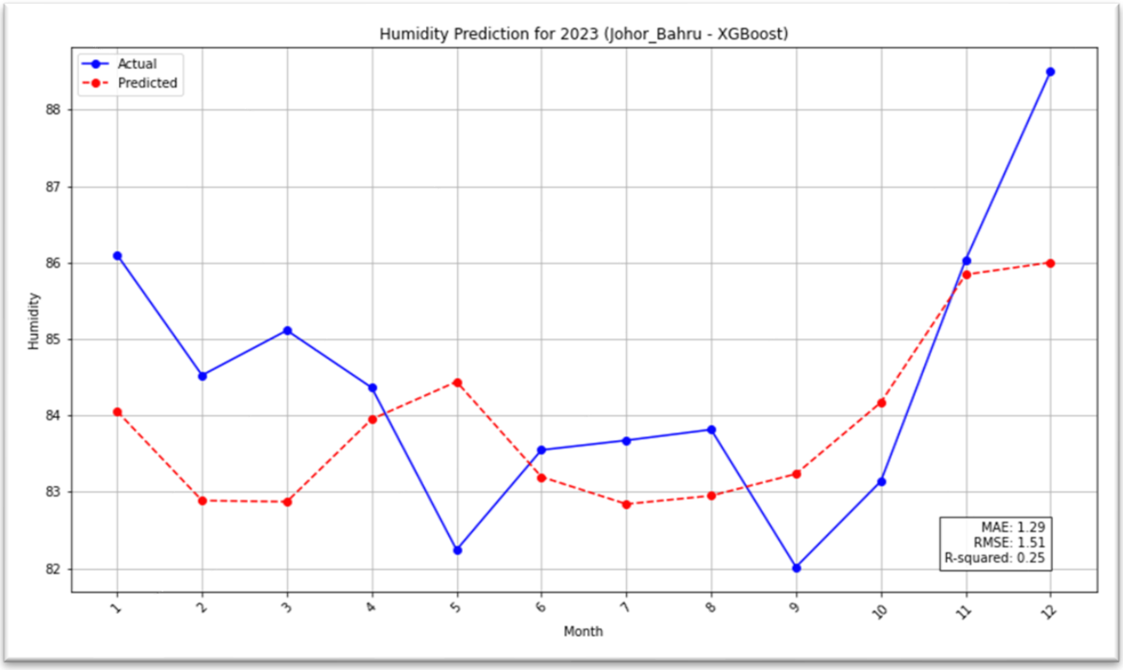

Figure 17: Humidity Prediction for 2023 (Johor Bahru - XGBoost)

Regarding rainfall predictions, both models struggled to accurately capture the high variability in rainfall patterns. The Random Forest model for rainfall prediction yielded an MAE of 79.67, RMSE of 93.56, and a negative R-squared value of -0.31.

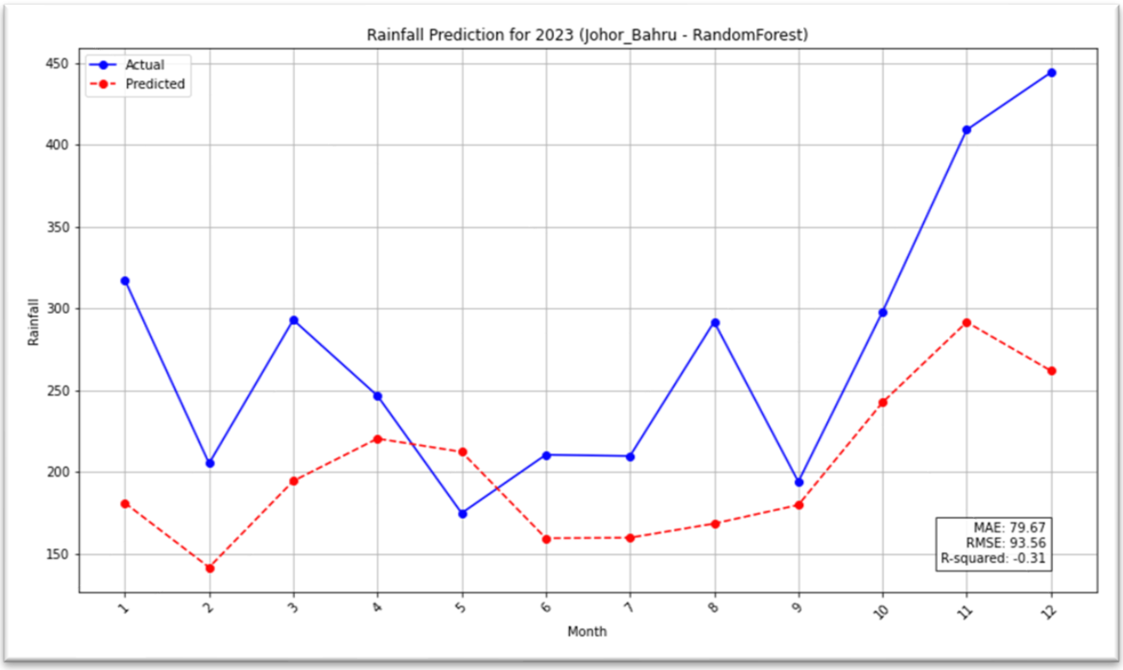

Figure 18: Rainfall Prediction for 2023 (Johor Bahru - Random Forest)

Similarly, the XGBoost model produced an MAE of 79.53, RMSE of 93.52, and the same negative R-squared value of -0.31. The negative R-squared values for both models indicate that they perform worse than a horizontal line for predicting rainfall, suggesting that the models are not capturing the underlying patterns effectively.

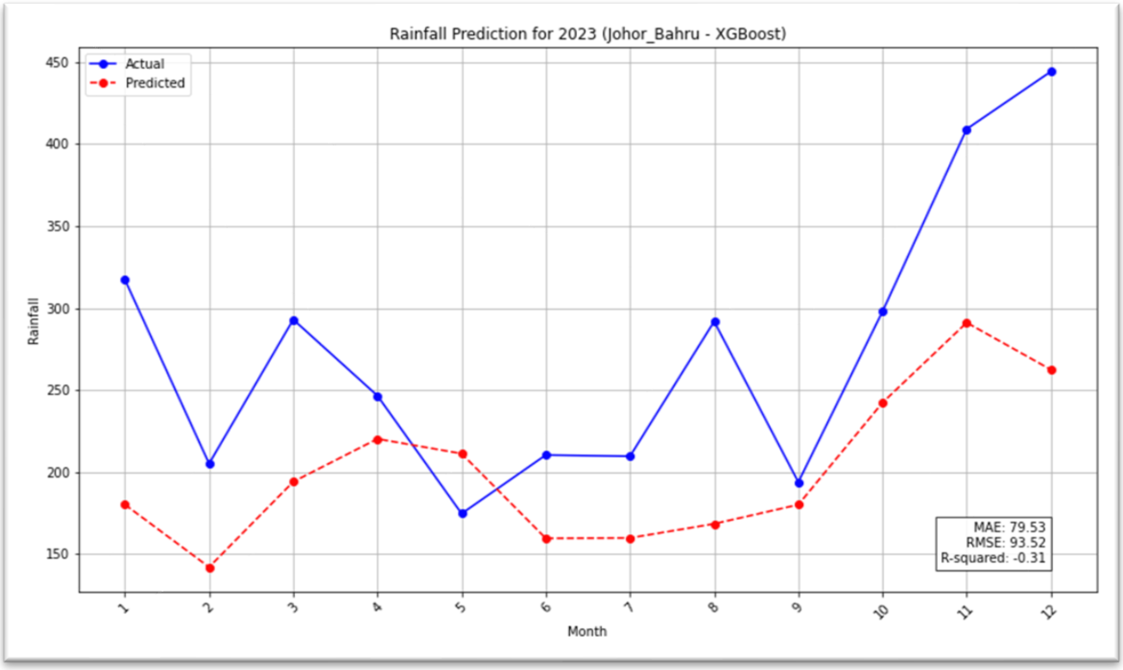

Figure 19: Rainfall Prediction for 2023 (Johor Bahru - XGBoost)

The visual representations in the graphs highlight the challenges both models face in predicting extreme values, particularly for rainfall. In the humidity graphs, both models show a general ability to follow the trend of actual humidity levels, but they struggle to capture the sharp increases or decreases, especially towards the end of the year. The rainfall graphs demonstrate a more significant disparity between predicted and actual values, with both models consistently underestimating rainfall amounts, especially during peak rainfall months.

The similar performance of Random Forest and XGBoost algorithms suggests that the limitation may lie in the features used for prediction rather than the choice of algorithm. The models' inability to accurately predict extreme events, particularly in rainfall, indicates a need for additional relevant features or a different approach to handling highly variable weather phenomena.

Both XGBoost (Figure 20) and Random Forest (Figure 21) models demonstrate similar performance in predicting temperature trends. The models accurately capture the overall seasonal pattern, with temperatures peaking around the fifth month and declining towards the end of the year. However, both models consistently underestimate the actual temperatures, particularly during the warmer months (months 4-10). The prediction accuracy appears to be higher during the cooler months at the beginning and end of the year.

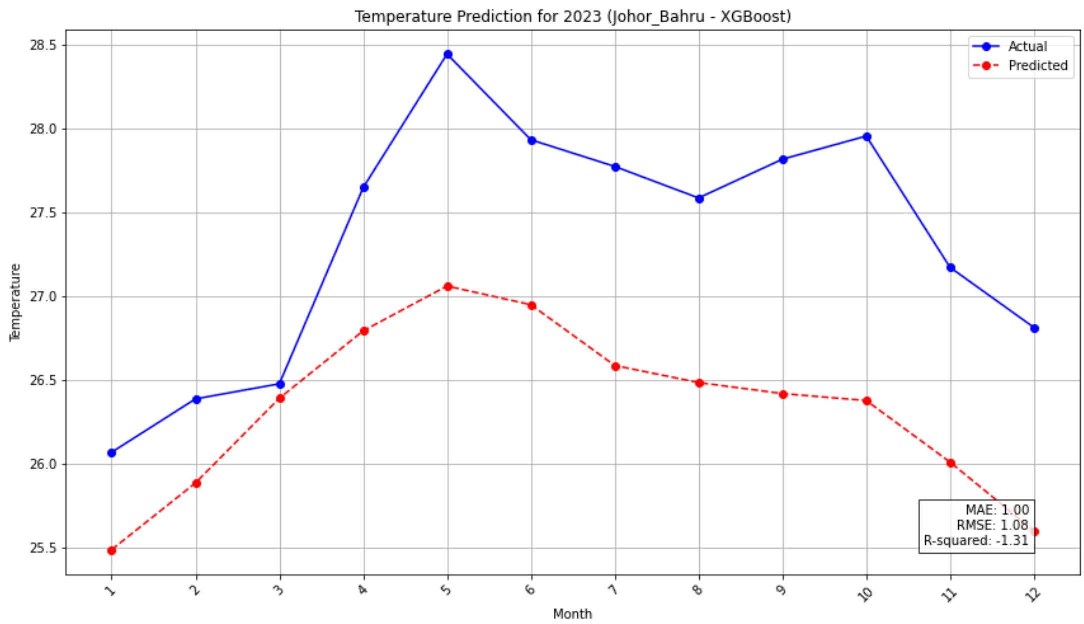

Figure 20: Temperature Prediction for 2023 (Johor Bahru - XGBoost)

The performance metrics for both models are identical, with a Mean Absolute Error (MAE) of 1.00, Root Mean Square Error (RMSE) of 1.08, and R-squared values of -1.30 and -1.31 for Random Forest and XGBoost, respectively. The negative R-squared values suggest that the models' predictions are less accurate than a horizontal line representing the mean of the observed data, indicating room for improvement in the models' predictive capabilities.

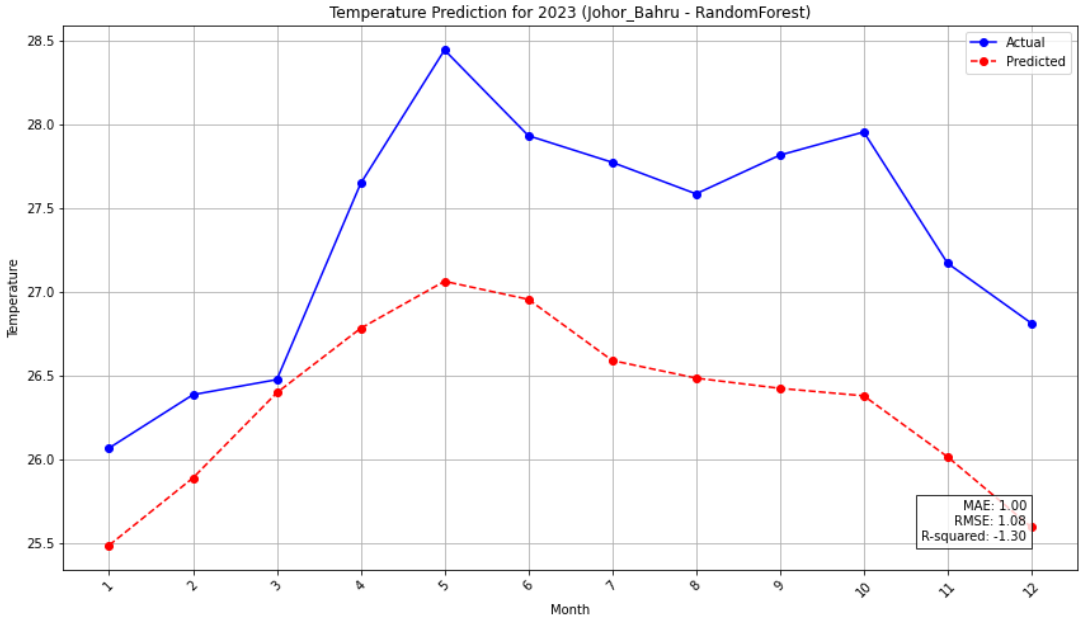

Figure 21: Temperature Prediction for 2023 (Johor Bahru - Random Forest)

The wind speed predictions, shown in Figure 22 (Random Forest) and Figure 24 (XGBoost), reveal more variability in both actual and predicted values compared to the temperature predictions. Both models capture the general trend of wind speed fluctuations throughout the year, with notable increases around months 4-5 and 10-11.

The models appear to struggle with predicting extreme values, often underestimating peaks and overestimating troughs in wind speed. This is particularly evident in months 2-3 and 8-9, where the actual wind speeds reach their lowest points.

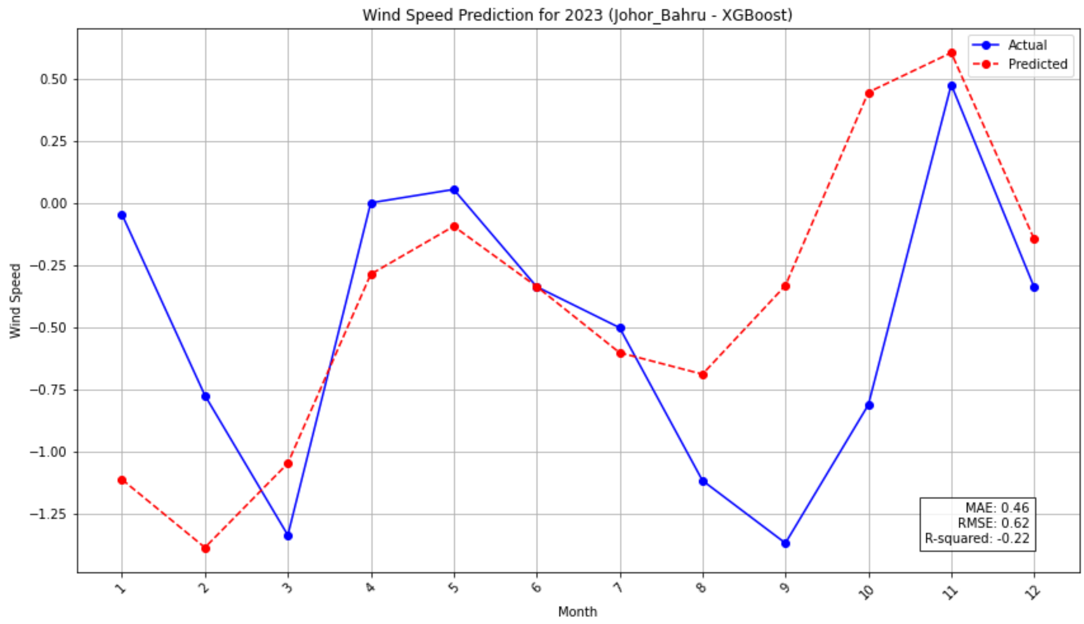

Figure 22: Wind Speed Prediction for 2023 (Johor Bahru-XGBoost)

The performance metrics for wind speed predictions are slightly better than those for temperature. Both models achieve an MAE of 0.46 and RMSE of 0.62. The R-squared values are -0.23 for Random Forest and -0.22 for XGBoost, which, while still negative, indicate marginally better performance compared to the temperature predictions.

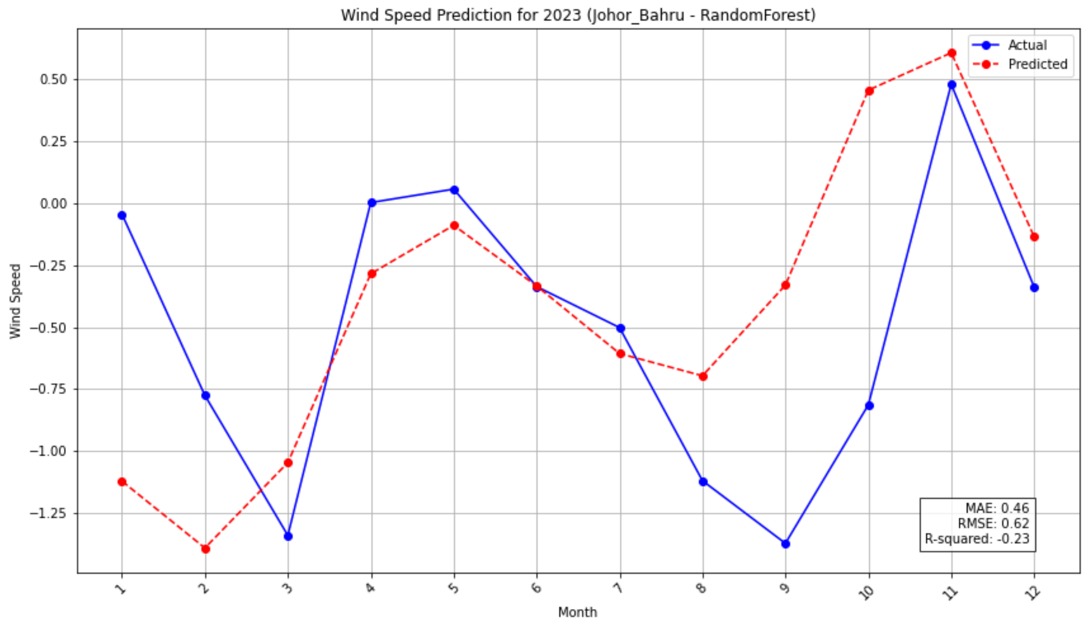

Figure 23: Wind Speed Prediction for 2023 (Johor Bahru-Random Forest)

In conclusion, while both models show some predictive capability for humidity, they struggle significantly with rainfall prediction. The high MAE and RMSE values, coupled with negative R-squared values for rainfall, underscore the complexity of weather prediction, especially for highly variable factors like rainfall. Future work could focus on incorporating additional relevant features, exploring more advanced time series models, or considering ensemble methods that might better capture the complex patterns in weather data.

4.8 Chapter Summary

In this chapter, the research experimental design and implementation of the proposed solution for preserving cultural heritage sites through microclimate monitoring and prediction are summarized. The steps for data collection, pre-processing, model development using Random Forest and XGBoost, evaluation and testing are outlined. The experimental setup and parameter details are provided, along with the evaluation metrics used to assess the performance of the models. The next chapter will present the results and analysis of the experiments, highlighting the insights gained and the recommendations for preserving cultural heritage sites.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Research Outcomes

This chapter presents the outcomes of the research conducted on preserving cultural heritage sites through the application of the Random Forest and XGBoost algorithms for microclimate monitoring and prediction. The research aimed to develop an effective and efficient approach to monitor and predict the microclimate conditions at cultural heritage sites, thereby aiding in the preservation of these sites for future generations.

One of the key research outcomes is the development of a microclimate monitoring system utilizing the Random Forest and XGBoost algorithms. The system collects real-time data from various sensors deployed at cultural heritage sites, including temperature, humidity, light intensity, and air quality. The collected data is then processed and analyzed using the Random Forest and XGBoost algorithms to identify patterns and trends in microclimate conditions.

Another significant outcome of this research is the achievement of accurate microclimate prediction at cultural heritage sites. By training the Random Forest and XGBoost algorithms on historical microclimate data, the developed system can forecast future microclimate conditions with a high degree of accuracy. This prediction capability enables heritage site managers and conservationists to proactively plan and implement appropriate preservation strategies based on anticipated changes in the microclimate.

5.2 Contributions to Knowledge

The research conducted in this thesis has made several contributions to the field of cultural heritage preservation and microclimate monitoring. These contributions include the application of machine learning algorithms, specifically the Random Forest and XGBoost algorithms, in the context of microclimate monitoring and prediction at cultural heritage sites. By demonstrating the effectiveness of these algorithms in capturing complex relationships between various environmental factors and microclimate conditions, this research provides valuable insights into the potential of machine learning techniques for heritage site preservation.

The research presents a comprehensive framework for monitoring and predicting microclimate conditions at cultural heritage sites. This framework integrates data collection, preprocessing, analysis, and prediction using the Random Forest and XGBoost algorithms. The developed framework can serve as a guide for future researchers and practitioners in the field of cultural heritage preservation, providing a structured approach to leveraging machine learning for microclimate management.

By accurately monitoring and predicting microclimate conditions, this research contributes to the development of improved preservation strategies for cultural heritage sites. The insights gained from the analysis of microclimate data can inform decision-making processes related to site maintenance, climate control, and artifact preservation, ultimately enhancing the long-term sustainability of these important cultural assets.

5.3 Future Works

While this research has achieved significant milestones in the preservation of cultural heritage sites through microclimate monitoring and prediction, there are several avenues for future research and development. Some potential areas of focus include the integration of additional data sources, such as weather forecasts, aerial imagery, and historical records, to further enhance the accuracy and reliability of microclimate prediction models. Incorporating these diverse data sets can provide a more comprehensive understanding of the factors influencing microclimate conditions and enable more robust decision-making processes.

Continued monitoring and analysis of microclimate conditions over extended periods can yield valuable insights into the long-term trends and impacts on cultural heritage sites. Future research should consider conducting longitudinal studies to capture the dynamic nature of microclimate conditions and evaluate the effectiveness of preservation strategies over time.

Encouraging collaboration and knowledge sharing among researchers, practitioners, and stakeholders in the field of cultural heritage preservation is crucial for advancing the application of microclimate monitoring and prediction techniques. Future research should focus on establishing platforms for collaboration, fostering interdisciplinary partnerships, and promoting the dissemination of research findings to maximize the impact on heritage site conservation efforts.

By addressing these future research directions, the field of microclimate monitoring and prediction for cultural heritage preservation can continue to evolve and contribute to the sustainable management of these invaluable cultural assets.

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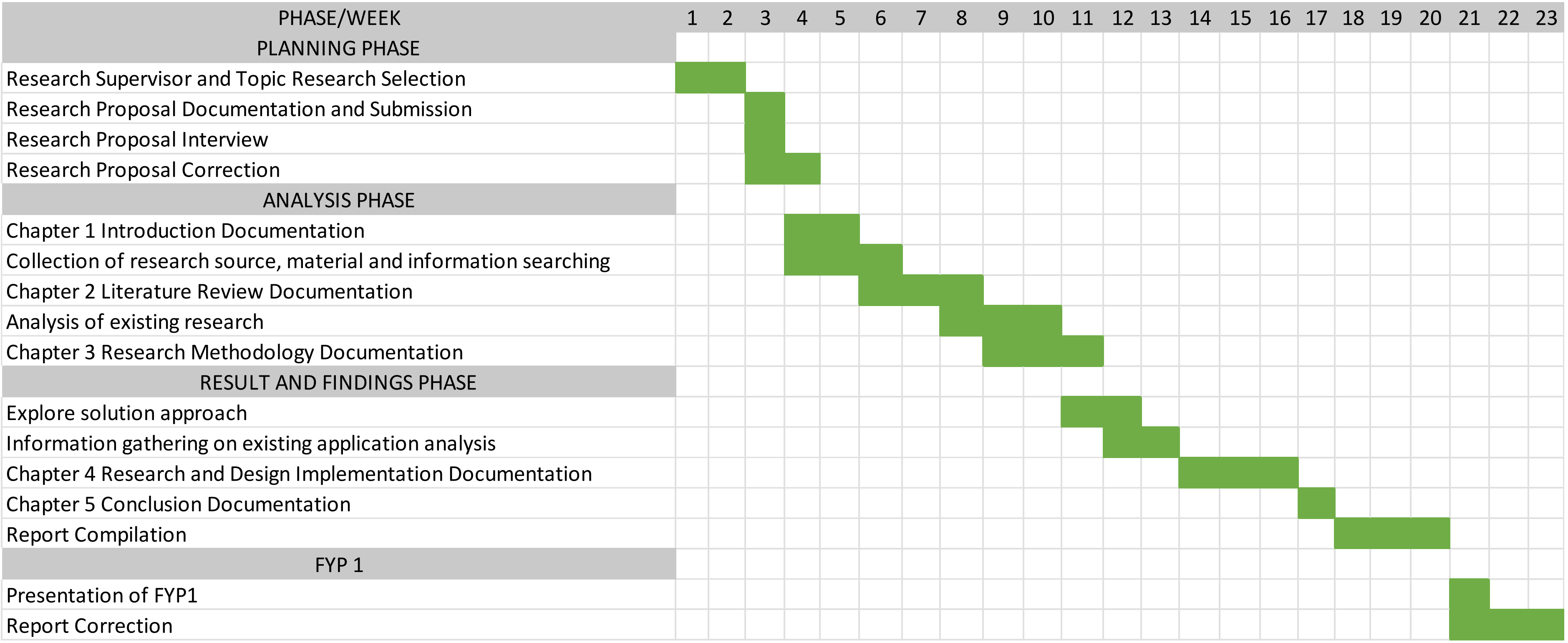
APPENDIX A: Gantt Chart for FYP 1



APPENDIX B: Gantt Chart for FYP 2