MICROCLIMATE DATA ANALYSIS AT CULTURAL HERITAGE SITES USING THE RANDOM FOREST AND XGBOOST ALGORITHMS

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USING THE RANDOM FOREST AND XGBOOST ALGORITHMS

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
Faculty of Engineering
Universiti Teknologi Malaysia

JULY 2024

DECLARATION

I declare that this thesis entitled *" Microclimate Data Analysis at Cultural Heritage Sites Using the Random Forest and XGBoost Algorithms"* is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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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

This study aims to develop an accurate prediction model for microclimate data in the heritage-rich cities of Johor Bahru and Melaka, Malaysia. The research focuses on key microclimate variables including temperature, rainfall, humidity, and wind speed. Historical data will be obtained from the Copernicus Climate Data Store to train and validate the prediction models. The study will compare the performance of two machine learning algorithms, Random Forest and XGBoost, to determine the most effective method for microclimate prediction in these specific urban environments. A user-friendly dashboard will be developed using HTML to visualize both historical data and predictions, making the information accessible and interpretable. The accuracy and reliability of the prediction models will be evaluated using standard statistical measures including Mean Absolute Error, Root Mean Square Error, and Coefficient of Determination score. The models will be trained using cross-validation techniques for hyperparameter tuning, and their performance will be assessed on a held-out test set representing the year 2023. This research aims to provide a valuable tool for local meteorologists, urban planners, and researchers interested in the microclimatic conditions of Johor Bahru and Melaka. The resulting predictive model and dashboard could serve as a foundation for future studies on the impact of microclimate on urban planning and heritage conservation in these historically significant Malaysian cities.

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 dan Melaka, 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. 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.

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LIST OF ABBREVIATIONS

ML	-	Machine Learning
AI	-	Artificial Intelligence
RF	-	Random Forest
CH	-	Cultural Heritage
LR	-	Logistic Regression
ANN	-	Artificial Neural Network
CNN	-	Convolutional Neural Network
KNN	-	K-Nearest Neighbour
XGBoost	-	Extreme Gradient Boosting
MAE	-	Mean Absolute Error
RMSE	-	Root Mean Square Error
R^2	-	Coefficient of Determination
CDS	-	Climate Data Dtore

CHAPTER 1

INTRODUCTION

1.1 Overview

CH 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 CH, 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 CH (Pioppi et al., 2020). Safeguarding worldwide CH 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 CH 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 (ML) algorithms, namely Random Forest (RF) and Extreme Gradient Boosting (XGBoost), for microclimate monitoring and prediction at CH sites. By leveraging these techniques, it aims to contribute to the preservation of CH sites under changing environmental conditions, supporting sustainable and efficient conservation efforts.

1.2 Problem Background

CH 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 and Melaka have 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 CH sites and various monuments. Consequently, striking a balance between consumption and conservation strategies presents increasing challenges for the effective management of CH sites (Buonincontri et al., 2017). Therefore, focusing on the preservation of CH and promoting sustainable tourism has become a primary objective recently to support both CH 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 CH sites and monuments in Johor Bahru and Melaka, by employing microclimate monitoring and prediction through the RF 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 RF and XGBoost algorithms were employed to analyze the impact of these factors on the preservation of CH sites.

1.4 Research Objectives

The following are the objectives proposed:

(a) To identify and compare the most suitable machine learning algorithms for analyzing microclimate data in CH sites.

(b) To evaluate the performance and accuracy of the developed machine learning models in predicting microclimate conditions.

(c) To design and develop a user-friendly dashboard for displaying microclimate data trends and predictions.

1.5 Research Scopes

The scope of this research project focuses on the preservation of the Sultan Ibrahim Building in Johor Bahru and A Famosa in Melaka using machine learning-based microclimate prediction. The primary objectives are to develop machine learning algorithms and a dashboard to collect, display, and analyze microclimate parameters, thereby assisting local authorities in planning preventive maintenance for these heritage sites. Specific areas included in the scope of this research are:

(a) Obtaining microclimate data from the Copernicus Climate Data Store (CDS) for the Sultan Ibrahim Building and A Famosa. The data will include parameters such as temperature, rainfall, humidity, and wind speed.

(b) Comparing the performance of two machine learning algorithms, RF and XGBoost, to determine the most suitable method for microclimate monitoring and prediction.

(c) Designing and developing a dashboard using HTML and JavaScript to display and analyze historical microclimate data trends and predictions.

(d) Evaluating the accuracy and effectiveness of the developed machine learning models and dashboard in assisting local authorities with planning more effective maintenance strategies for the heritage sites.

1.6 Research Contribution

A thorough literature review on microclimate impacts on CH sites reveals that many researchers have utilized 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 RF and XGBoost algorithms, along with the comprehensive analysis of temperature, humidity, and wind speed, has not yet been applied in the context of heritage site preservation. Therefore, this study offers a novel contribution to the machine learning field, particularly in modeling microclimate threats and conducting risk assessments for CH sites.

Given the current changing climate and landscape, this study is highly relevant and significantly contributes to the sustainable management of CH resources. Climate change poses a considerable threat to the integrity of heritage sites due to its impact on key environmental factors such as temperature, rainfall, humidity, and wind speed. These changes can increase the vulnerability and potential damage to cultural assets. This study provides valuable insights and technical guidance on 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 are expected to have practical applications for professionals involved in land use planning, landscape management, archaeological preservation, and public administration. These professionals can utilize the study's evidence-based strategies to manage CH sites and promote environmental sustainability effectively. By monitoring and predicting microclimate changes using RF and XGBoost algorithms, stakeholders can better preserve and protect CH sites for future generations.

1.7 Report Organization

This report is organized into six chapters. Chapter 1 introduces the topic of preserving CH sites through microclimate monitoring and prediction using RF and XGBoost algorithms, along with the research background, objectives, and the purpose of the study in Johor Bahru and Melaka. Chapter 2 reviews relevant literature on microclimate monitoring, including the assessment of temperature, rainfall, humidity, and wind speed, and compares various machine learning techniques for processing and analyzing data from heritage sites. Chapter 3 outlines the research methodology, detailing how the study employs RF and XGBoost algorithms to measure and analyze microclimate data for the preservation of CH sites. Chapter 4 presents the experimental setup and results, explaining how the experiments were conducted to derive insights from the microclimate data. Chapter 5 focuses on the development of the dashboard, showcasing the analyzed data and visualizing trends and predictions to provide a practical tool for local authorities. Finally, Chapter 6 summarizes the study, highlighting key findings and implications for the preservation of CH sites through microclimate monitoring and prediction, and offers recommendations for future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction to Case Study

Climate change has emerged as a significant global challenge, impacting various sectors, including the preservation of CH sites. The increasing frequency and intensity of extreme weather events, along with gradual shifts in temperature, humidity, and wind patterns, underscore the need for adaptive solutions to safeguard these invaluable assets. One promising approach involves applying advanced algorithms, such as RF and XGBoost, for microclimate monitoring and prediction at CH sites. These techniques can help preserve and protect these valuable assets by analyzing temperature, humidity, and wind speed data, crucial factors in their conservation.

This case study focuses on the implementation of RF and XGBoost algorithms for microclimate monitoring and prediction at two CH sites: the Sultan Ibrahim Building in Johor Bahru and A Famosa in Melaka. 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 collaborate to develop improved strategies for preserving CH sites like the Sultan Ibrahim Building and A Famosa under changing environmental conditions. By adopting a collaborative approach, the protection and preservation of these invaluable assets for future generations can be ensured, despite the challenges posed by climate change.

2.2 Importance of Preserving Cultural Heritage Sites

The preservation of CH sites holds immense significance for society, history, and identity, as these sites serve as tangible reminders of the shared past, providing valuable insights into the cultural, social, and economic development of human civilizations (Lowenthal, 1985). Protecting and maintaining these sites ensures the continuity of cultural memory and allows future generations to appreciate and learn from the rich tapestry of human history (UNESCO, 1972). Moreover, CH 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 CH 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 CH 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 CH 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 CH sites is crucial for developing effective preservation strategies. Identifying and mitigating the risks associated with these factors allows for better protection of these invaluable resources, ensuring their continued existence for future generations.

2.4 Traditional Methods for Cultural Heritage Sites Preservation

Traditional methods for CH 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 CH 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 CH 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, CH 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 CH 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 RF, which are both capable of achieving these requirements.

2.5.1 Random Forest

Breiman's RF 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) (Figure 1). Unlike other learning methods, RF is designed to manage complex datasets with high dimensionality, noisy, and missing data, making it particularly useful for microclimate monitoring and prediction at CH sites.

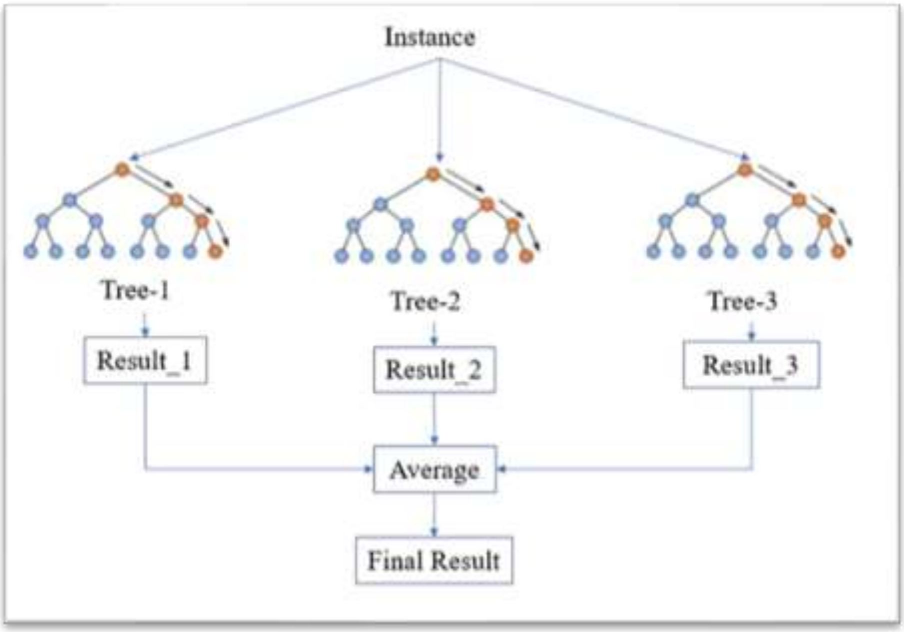

Figure 1: Random Forest Model Architecture

Each decision tree in a RF 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.

RF's robustness and high-performance capabilities have made it a popular choice in various fields, including image analysis, remote sensing, and ecology.

Furthermore, RF 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 CH 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 RF is its ability to manage interactions between variables, which is important in predicting microclimate parameters at CH 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 CH sites, where environmental conditions can vary significantly and interactions between environmental factors can be complex.

In conclusion, RF is a powerful machine learning algorithm that has proven to be a valuable tool for microclimate monitoring and prediction at CH 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

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 (Figure 2). The result is a highly accurate classifier that can manage large and complex datasets.

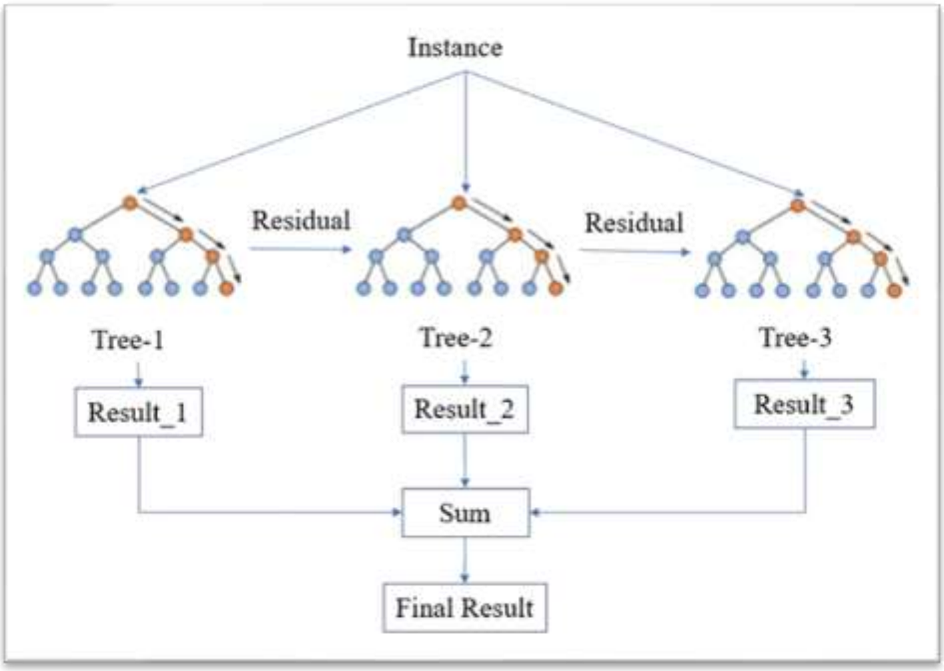

Figure 2: XGBoost Model Architecture

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 RF 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 CH 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 CH 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 CH 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 CH sites, enabling them to develop more effective strategies for managing and preserving these invaluable assets for future generations.

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

Several studies in the CH 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 CH 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 XGBoost model was the most suitable approach.

Table 1: 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 RF 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, RF, 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 RF but found that it did not accurately predict the levels of dangerous pollutants. However, RF had the advantage of working with incomplete datasets. Pasupuleti et al. (2020) compared Decision Tree, Linear Regression, and RF for predicting air pollutant levels using meteorological conditions and data from the Arduino platform. RF provided more accurate results due to reduced overfitting and error. However, it required more memory and incurred higher costs.

In summary, XGBoost and RF 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	RF
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^2 (Caruana & Niculescu-Mizil, 2006)	Compare using MAE, RMSE, R^2 (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 CH sites through machine learning-based microclimate monitoring, with a specific focus on the application of RF 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 CH sites and the importance of their preservation. It then explores the impact of microclimate factors on CH 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 RF and XGBoost, and their application in this study. The review highlights the significance of using machine learning-based approaches for preserving CH sites and the potential benefits of incorporating them into preservation strategies.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This section delves into the methodological approach employed in the study, encompassing the research design framework, procedures, and techniques utilized. The investigation follows a four-phase workflow, which will be explored in detail throughout this chapter. Each component of the framework will be thoroughly examined, providing insights into its implementation within the context of the research. Additionally, the specific techniques applied at every stage of the process will be detailed. This comprehensive overview aims to offer a clear understanding of the systematic approach underpinning the study, detailing how each step contributes to addressing the research objectives.

3.2 Research Phase

The research methodology framework has four main phases which are Literature Review, Data Collection and Preprocessing, Machine Learning Model Development and Dashboard Development. 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. The framework then continues with the second phase which is the data collection and preprocessing phase of the research. The next phase is the machine learning model development phase which is the part where the algorithm is develop. The last phase is the dashboard development and analysis of result phase where end results will be reported.

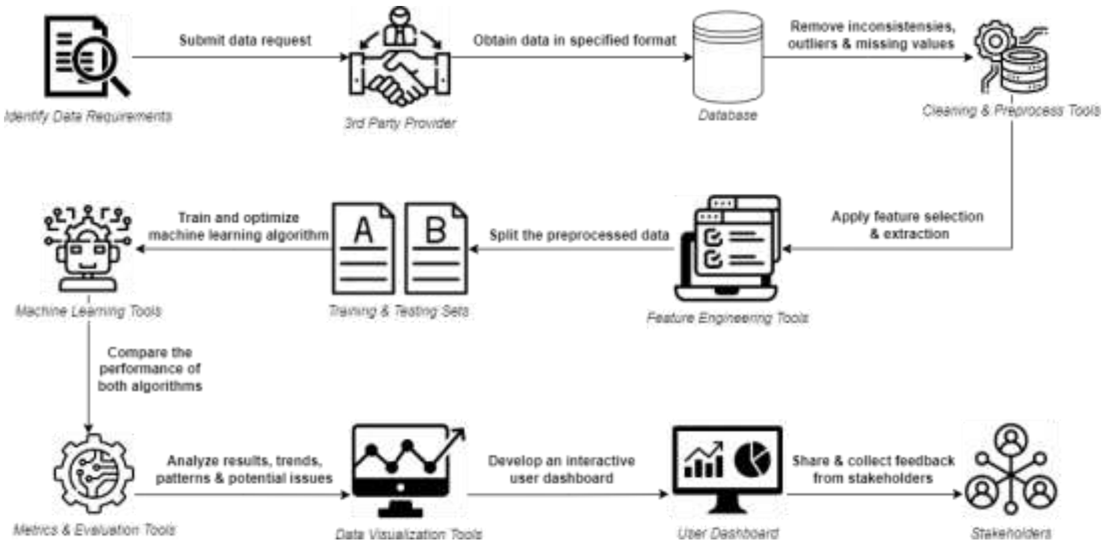

Figure 3: Research Phase

3.2.1 Phase 1: Literature Review

In the first phase, a comprehensive literature review is conducted to gather relevant information on preserving CH sites through microclimate monitoring and prediction using RF 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 CDS for a specific heritage site in Johor Bahru and Melaka. This data, encompassing temperature, relative humidity, rainfall, 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 RF 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 MAE and RMSE, to assess their predictive capabilities. This evaluation process helps determine the effectiveness and performance of the RF 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 and Analysis of Result

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 rainfall, 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, HTML dashboard is 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 CH 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 CDS, data pre-processing techniques, machine learning algorithms (RF 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 the Copernicus CDS is essential for understanding the environmental conditions at the heritage site. The data includes monthly measurements of temperature, humidity, rainfall, and wind speed from 1940 to 2023. These parameters are crucial for assessing the impact of environmental factors on the site's structural integrity and identifying potential maintenance issues. The data for 2024 is available but only up to June; therefore, predicting the 2023 data allows for comparison with the actual data for that year.

The research utilizes machine learning techniques to analyze the collected microclimate data and develop predictive models for preventive maintenance. RF and XGBoost algorithms were chosen due to their proven effectiveness in handling complex relationships between variables and managing both regression and classification tasks. However, regressors were specifically chosen over classifiers in this study to predict continuous microclimate variables, providing more precise and actionable predictions for future microclimate conditions. Python was selected for implementing these machine learning algorithms due to its robustness and extensive libraries that facilitate data manipulation and analysis. The following Python tools and libraries were employed: Spyder, an Integrated Development Environment (IDE) used for writing and running Python code; Pandas, for data manipulation and analysis, particularly for handling large datasets; NumPy, for numerical computations and efficient array handling; Scikit-learn (sklearn), which provides a wide range of machine learning algorithms, including RF and XGBoost; and also Matplotlib and Seaborn, used for data visualization, creating plots and graphs that help in understanding the data and the results of the analysis.

The development of a user-friendly dashboard integrating microclimate data and machine learning models provides a powerful tool for monitoring and maintenance planning. The dashboard is developed using HTML, JavaScript, and CSS, enabling interactive and dynamic visualizations. The graphs, plots, and heatmaps within the HTML 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.

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 RF and XGBoost algorithms. The final phase focused on developing a user-friendly dashboard that visualizes the microclimate data and provides maintenance recommendations.

CHAPTER 4

EXPERIMENTAL DESIGN AND SETUP

4.1 Introduction

This chapter discusses in depth the experimental setup and result 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, 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 Data Store (CDS), 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, rainfall, humidity, and wind speed. Two machine learning algorithms, RF and XGBoost, will be implemented and compared for their performance in microclimate monitoring and prediction. Additionally, a dashboard will be designed and developed using HTML, Javascript and CSS to display the analysis of 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 Sultan Ibrahim Building, Johor Bahru and A Famosa, Melaka

4.3 Research Framework

In this section, the process of downloading, extracting, and processing microclimate data from the Copernicus CDS is outlined, followed by the generation of various analyses and visualizations. The dataset covering the period from 1940 to 2023 for each microclimate parameter was downloaded from the CDS in NetCDF format, a standard format for storing multidimensional scientific data. To convert the NetCDF files into a more usable format, a Python script, referred to as Script 20, was employed. This script extracts the data into DAT files, such as Extract-194001.dat for the January 1940 Rain dataset. Each DAT file consists of three columns: latitude, longitude, and the microclimate data. The script outputs all the latitude and longitude coordinates along with the corresponding microclimate data for each observed area.

The DAT files generated by Script 20 were then used as input for Script 54, which processes these files to plot the monthly data, specifically creating heatmaps of monthly accumulated microclimate data for each month of the desired year. Subsequently, Script 60 was employed to extract data for specific latitude and longitude coordinates, such as those for the 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 the Sultan Ibrahim Building, the output file includes columns for the year and month, the chosen latitude and longitude, the nearest latitude and longitude from the data, and the corresponding microclimate data. Each month's data is saved in separate files, and data for different years is organized into distinct folders. Finally, script 80 was then utilized to merge the datasets from various files into a comprehensive dataset, facilitating further analysis.

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, RF 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 RF 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.

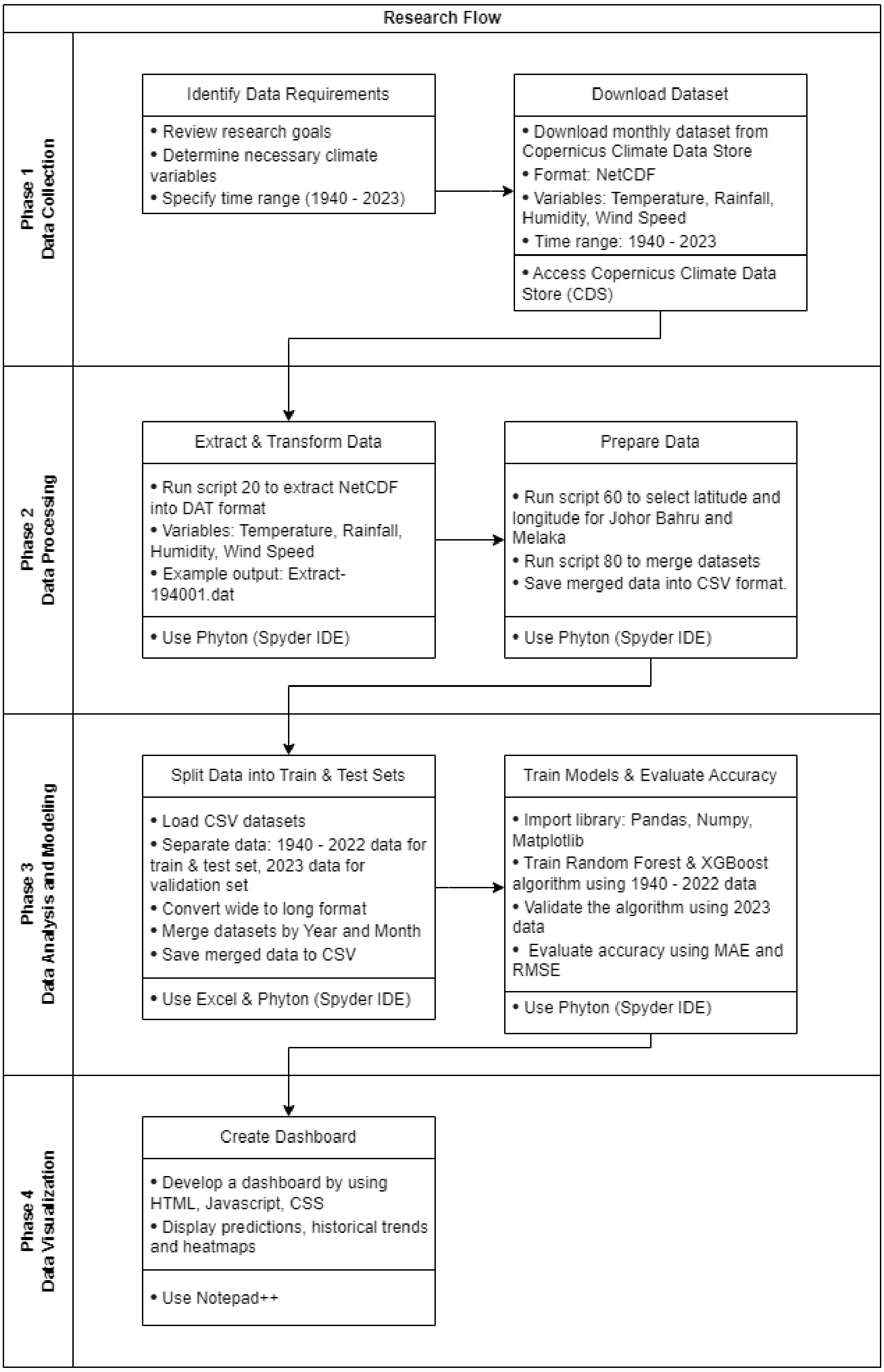

Figure 4: Research Framework

4.4 Study Area

The research focuses on two significant CH sites in Malaysia. The first site is the Sultan Ibrahim Building in Johor Bahru (Figure 5), an iconic administrative building built in the early 20th century. This building stands as a prime example of colonial architecture, located at approximately 1.4616° N, 103.7622° E. The second site is A Famosa in Melaka (Figure 6), a 16th-century Portuguese fortress located in the historic city. It is one of the oldest surviving European architectural remains in Southeast Asia, situated at approximately 2.1936° N, 102.2501° E. Both sites are subject to the tropical climate of Malaysia, characterized by high temperatures, humidity, and significant rainfall throughout the year.

Figure 5: Sultan Ibrahim Building, Johor Bahru

Sultan Ibrahim Building in Johor Bahru and A Famosa in Melaka were chosen as study areas due to their significance as heritage sites in Malaysia. Johor Bahru, with its rich history and cultural landmarks, provides an excellent starting point. However, studying just one location would limit the diversity of the data. To broaden the analysis, Melaka was included, known for its cultural and historical treasures. This choice allows for a comparison of microclimate data between two different regions.

Figure 6: A Famosa, Melaka

4.5 Data Collection and Extraction

In this research study, the microclimate data was obtained from the ECMWF Reanalysis v5 (ERA5) dataset, provided by the Copernicus CDS 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, Spyder, a powerful Integrated Development Environment (IDE) for Python, was utilized, facilitating efficient data handling and analysis.

For this research, microclimate data spanning a substantial time range, from 1940 to 2023, was collected. This extended historical period allowed for the gathering of significant amounts 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, valuable insights can be gained into the site's microclimate dynamics, including temperature, humidity, wind speed, and rainfall. These insights are essential for developing effective strategies to preserve and protect the heritage site from potential environmental impacts.

4.5.1 Data Collection

The data was collected from the Climate Data Store (CDS) Copernicus website. The chosen dataset for this research is the ERA5 monthly averaged data on single levels from 1940 to the present. A single level was selected because the CDS indicates that this dataset is more suitable for forecasting compared to datasets on pressure levels. Therefore, for rainfall, humidity, temperature, and wind speed, the monthly data from 1940 to 2023 was downloaded at the specified time (00:00 UTC) and covered a defined geographical area. The data was 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 7. The script loops through a list of month names (e.g., 'Jan', 'Feb', 'Mar', etc.) and opens each corresponding NetCDF file containing microclimate data for that month. It reads the latitude, longitude, and microclimate 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 microclimate data and converts it from Kelvin to Celsius. It then creates a grid of latitude and longitude values using np.meshgrid and combines the microclimate 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 microclimate 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-Extract' located in the current working directory. Overall, this script is designed to extract and process microclimate 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.

```python
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

,

The script in Figure 9 is designed to visualize monthly average microclimate 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 microclimate data files, processes them to extract latitude, longitude, and microclimate values, and creates a contour plot of the microclimate 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.

```python
# 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 Accumulated Data

Additionally, it overlays administrative boundaries of Malaysian states obtained from a shapefile. The script utilizes a colormap to represent microclimate 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 microclimate patterns for a chosen region, aiding in understanding climate variations over time.

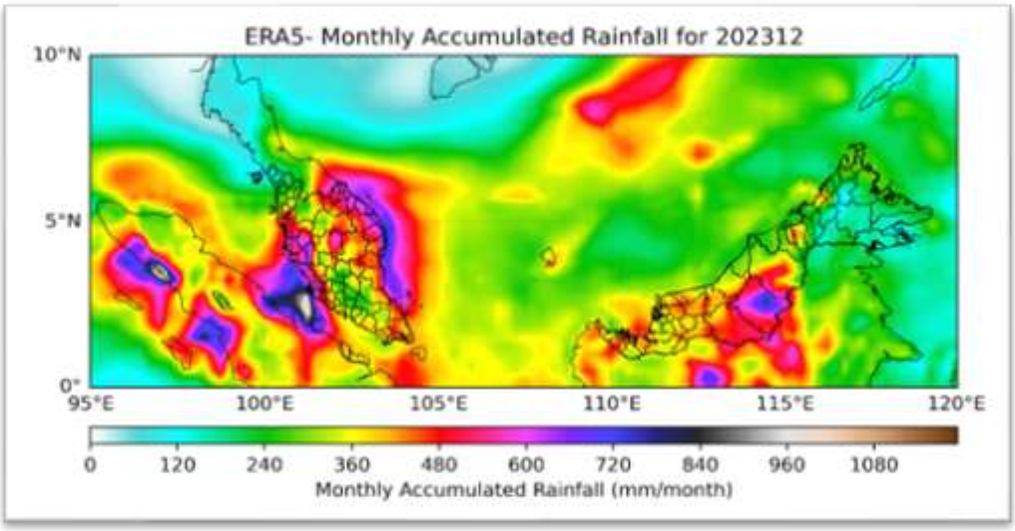

Figure 10: Monthly Accumulated Data Sample – Rainfall Heatmap

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 microclimate parameters like temperature, humidity wind speed 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.

```python
# 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 microclimate parameters. It then extracts the relevant temperature, humidity, wind speed 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 microclimate data values for each month.

```
# 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 as the sample shown in Figure 13 below. 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

4.5.2 Splitting of Data into Training and Testing Sets

In this research study, the provided code for data processing and saving facilitates the preparation of datasets for machine learning model training and testing. The function process_and_save_data is responsible for loading and preprocessing multiple types of microclimate data (temperature, humidity, rainfall, and wind speed) and merging them into a single dataset. Initially, the function reads in the CSV files containing temperature, humidity, rainfall, and wind speed data for a given location. Each dataset is then melted from a wide format to a long format, where each row represents a single observation (Year, Month, Value). This step ensures that the data is in a consistent format for merging.

```python
    # Apply month mapping
    temperature_melted['Month_Num'] = temperature_melted['Month'].map(month_mapping)
    humidity_melted['Month_Num'] = humidity_melted['Month'].map(month_mapping)
    rainfall_melted['Month_Num'] = rainfall_melted['Month'].map(month_mapping)
    wind_speed_melted['Month_Num'] = wind_speed_melted['Month'].map(month_mapping)

    # Merge all the dataframes on Year and Month_Num
    merged_data = pd.merge(temperature_melted, humidity_melted, on=['Year', 'Month', 'Month_Num'])
    merged_data = pd.merge(merged_data, rainfall_melted, on=['Year', 'Month', 'Month_Num'])
    merged_data = pd.merge(merged_data, wind_speed_melted, on=['Year', 'Month', 'Month_Num'])

    # Drop the 'Month_Num' column as it is no longer needed
    merged_data = merged_data.drop(columns=['Month_Num'])

    # Create historical data excluding 2023 and 2024
    historical_data = merged_data[(merged_data['Year'] < 2023)]

    # Create actual data for 2023
    actual_data_2023 = merged_data[(merged_data['Year'] == 2023)]

    # Save to CSV files
    historical_data.to_csv(historical_output_file, index=False)
    actual_data_2023.to_csv(actual_output_file, index=False)

# Process data for JB
process_and_save_data(
    'temperature_data_jb.csv',
    'humidity_data_jb.csv',
    'rainfall_data_jb.csv',
    'wind_data_jb.csv',
    'historical_data_jb_2022.csv',
    'actual_data_jb_2023.csv'
```

Figure 14: Split the pre-processed data into training and testing sets

A dictionary mapping month names to numeric values is applied to convert month names into numerical representations, which aids in the merging process. The reshaped datasets are merged into a single dataframe on the columns 'Year' and 'Month_Num', consolidating all microclimate variables into one dataset. The merged dataset is then filtered to exclude data from 2023 and beyond, creating the historical data subset which is saved as a CSV file for training purposes. Additionally, data specific to the year 2023 is extracted and saved separately, representing the actual data for testing and validation.

In this context, the split into training and testing sets is achieved by separating historical data (up to 2022) and recent data (2023). This approach ensures that the model is trained on past data and tested on the most recent data, simulating a real-world scenario where future predictions are made based on historical patterns. Splitting data into training and testing sets is essential for model validation, preventing overfitting, and ensuring reliable performance metrics. It allows for the evaluation of the model's performance on unseen data, providing an estimate of how well the model generalizes to new data. By training the model on one subset and testing on another, we can detect overfitting, where the model performs well on training data but poorly on test data. This systematic approach to data preprocessing, merging, and splitting lays the groundwork for robust machine learning model development and evaluation in the context of microclimate data analysis.

4.6 Data Analysis and Modelling

This section outlines data analysis and modelling steps in this research. The process involved data preprocessing, feature engineering, model training, evaluation, and visualization. These steps ensured the development of accurate and robust machine learning models for climate variable prediction.

4.6.1 Data Preprocessing

The first step in the experimental setup was to preprocess the data. The read_and_preprocess_data function was utilized to load and preprocess both historical and actual data. This function mapped month names to numerical values, excluded specific years if necessary, and handled missing values. The code snippet in Figure 15 below illustrates this process.

```python
# Function to read and preprocess data
def read_and_preprocess_data(data_file, exclude_year=None):
    data = pd.read_csv(data_file)

    month_mapping = {
        'January': 1, 'February': 2, 'March': 3, 'April': 4,
        'May': 5, 'June': 6, 'July': 7, 'August': 8,
        'September': 9, 'October': 10, 'November': 11, 'December': 12,
        'Jan': 1, 'Feb': 2, 'Mar': 3, 'Apr': 4,
        'May': 5, 'Jun': 6, 'Jul': 7, 'Aug': 8,
        'Sep': 9, 'Oct': 10, 'Nov': 11, 'Dec': 12
    }

    data['Month_Num'] = data['Month'].map(month_mapping)

    if exclude_year is not None:
        data = data[data['Year'] != exclude_year]

    return data
```

Figure 15: Read and Preprocess Data

4.6.2 Feature Engineering

Feature engineering involved creating lagged features, rolling averages, seasonality features, and interaction terms. This was implemented in the prepare_data function. Lagged features captured temporal dependencies, rolling averages smoothed out short-term fluctuations, seasonality features accounted for cyclical patterns, and interaction terms provided additional predictive power. The implementation is as in the Figure 16 below.

```python
# Function for feature engineering
def prepare_data(data, variable):
    # Create lagged features
    for var in ['Temperature', 'Humidity', 'Rainfall', 'Wind Speed']:
        data[f'{var}_lag1'] = data.groupby('Year')[var].shift(1)
        data[f'{var}_lag2'] = data.groupby('Year')[var].shift(2)

    # Create rolling averages
    for var in ['Temperature', 'Humidity', 'Rainfall', 'Wind Speed']:
        data[f'{var}_rolling3'] = data.groupby('Year')[var].rolling(window=3, min_periods=1).

    # Create seasonality features
    data['month_sin'] = np.sin(2 * np.pi * data['Month_Num']/12)
    data['month_cos'] = np.cos(2 * np.pi * data['Month_Num']/12)

    # Create interaction terms
    data['temp_humid'] = data['Temperature'] * data['Humidity']
```

Figure 16: Feature Engineering

4.6.3 Data Quality Check

Ensuring data quality was paramount before training the models. The check_data_quality function checked for the presence of NaN or infinity values in the features and target variable. This process is essential to ensure the integrity of the dataset.

```python
# Function to check data quality
def check_data_quality(X, y):
    print("Checking for NaN or infinity values:")
    print("X contains NaN:", X.isna().any().any())
    print("y contains NaN:", y.isna().any())
    print("X contains infinity:", np.isinf(X).any().any())
    print("y contains infinity:", np.isinf(y).any())
```

Figure 17: Data Quality Check

4.6.4 Training of Machine Learning Models

For training the models, the data were first prepared by creating lagged features for each climate variable and splitting the data into training and testing sets. The training set included historical data, while the testing set consisted of data from 2023. The RF model was trained with hyperparameter tuning using GridSearchCV, tuning parameters such as the number of trees (n_estimators), maximum depth of the trees (max_depth), minimum samples required to split a node (min_samples_split), and minimum samples required at each leaf node (min_samples_leaf). Similarly, the XGBoost model was trained with hyperparameter tuning, where the parameters tuned were the number of trees (n_estimators), learning rate, maximum tree depth (max_depth), and minimum sum of instance weight needed in a child (min_child_weight). The hyperparameter tuning process involved a grid search with cross-validation to ensure the best combination of parameters for optimal performance.

```python
def train_model(X_train, y_train):
    param_grid = {
        'n_estimators': [100, 200, 300],
        'max_depth': [None, 10, 20, 30],
        'min_samples_split': [2, 5, 10],
        'min_samples_leaf': [1, 2, 4]
    }

    rf = RandomForestRegressor(random_state=42)

    grid_search = GridSearchCV(estimator=rf, param_grid=param_grid,
                               cv=5, n_jobs=-1, verbose=2, scoring='neg_mean_squared_error')

    grid_search.fit(X_train, y_train)

    print("Best parameters for Random Forest:", grid_search.best_params_)
    return grid_search.best_estimator_

# Function to train XGBoost models with hyperparameter tuning
def train_xgboost_model(X_train, y_train):
    param_grid = {
        'n_estimators': [100, 200, 300],
        'learning_rate': [0.01, 0.1, 0.3],
        'max_depth': [3, 5, 7],
        'min_child_weight': [1, 3, 5]
    }

    xgb = XGBRegressor(random_state=42)

    grid_search = GridSearchCV(estimator=xgb, param_grid=param_grid,
                               cv=5, n_jobs=-1, verbose=2, scoring='neg_mean_squared_error')

    grid_search.fit(X_train, y_train)

    print("Best parameters for XGBoost:", grid_search.best_params_)
    return grid_search.best_estimator_
```

Figure 18: Train Random Forest and XGBoost

4.6.5 Model Evaluation

Evaluating the accuracy of the trained models is crucial to understanding their predictive performance. Multiple metrics and cross-validation techniques were used for this purpose. The metrics included Mean Absolute Error (MAE), which measures the average magnitude of errors in predictions without considering their direction; Root Mean Squared Error (RMSE), which measures the square root of the average of squared differences between predicted and actual values, giving higher weight to larger errors; and Coefficient of Determination (R^2), which indicates the proportion of the variance in the dependent variable predictable from the independent variables.

TimeSeriesSplit was employed for cross-validation to maintain the temporal order of the data. This method ensures that the model is evaluated on future data points that were not seen during training, providing a realistic estimate of its performance in real-world scenarios. The cross-validation process involved splitting the data into multiple training and testing sets and computing the evaluation metrics for each fold. The average of these metrics was then used to assess the overall performance of the model.

```
# Function to evaluate predictions against actual data
def evaluate(predictions, actual_data):
    mae = mean_absolute_error(actual_data, predictions)
    rmse = np.sqrt(mean_squared_error(actual_data, predictions))
    r2 = r2_score(actual_data, predictions)

    metrics = {'MAE': mae, 'RMSE': rmse, 'R-squared': r2}
    return metrics

# Function to evaluate with cross-validation
def evaluate_with_cv(X, y, model, n_splits=5):
    tscv = TimeSeriesSplit(n_splits=n_splits)
    metrics = {'MAE': [], 'RMSE': [], 'R-squared': []}

    for train_index, test_index in tscv.split(X):
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]

        model.fit(X_train, y_train)
        predictions = model.predict(X_test)

        fold_metrics = evaluate(predictions, y_test)
        for key in metrics:
            metrics[key].append(fold_metrics[key])

    # Average the metrics across folds
    return {key: np.mean(values) for key, values in metrics.items()}
```

Figure 19: Evaluate the Accuracy of Random Forest and XGBoost

4.6.6 Prediction and Visualization

After training and evaluation, the models were used to make predictions. The predict function generated predictions, and the create_combined_plots function visualized the results, comparing actual and predicted values.

```python
# New function to create combined plots
def create_combined_plots(predictions, actual_data, months, variables, location, models, save_dir, metrics
    fig = plt.figure(figsize=(20, 20))
    gs = gridspec.GridSpec(4, 2, figure=fig)

    for i, variable in enumerate(variables):
        for j, model in enumerate(models):
            ax = fig.add_subplot(gs[i, j])

            ax.plot(months, actual_data[variable], marker='o', linestyle='-', color='b', label='Actual')
            ax.plot(months, predictions[f'{variable}_{model}'], marker='o', linestyle='--', color='r', lab

            ax.set_xlabel('Month')
            ax.set_ylabel(variable)
            ax.set_title(f'{variable} - {model}')
            ax.set_xticks(range(1, 13))
            ax.set_xticklabels([str(month) for month in range(1, 13)], rotation=45)
            ax.legend()
            ax.grid(True)
```

Figure 20: Create Plots and Accuracy Results

4.7 Dashboard Development

The Johor Bahru Dashboard in Figure 21 and Melaka Dashboard in Figure 22 was developed using HTML, JavaScript, and CSS to provide an intuitive visualization of the microclimate data and predictions for the CH sites. It features multiple interactive components, including selectable weather parameters, live weather display, and various charts showing predicted values, historical trends, and correlations between climate variables. The dashboard presents data through bar charts, line graphs, scatter plots, and heatmaps, offering a comprehensive view of both historical patterns and future predictions. Key elements include the actual vs predicted value for 2023, prediction for 2024, average monthly trends from 1940-2023, anomaly plots, and a correlation matrix to illustrate relationships between different weather parameters. The interface allows users to easily switch between different heritage sites and weather variables, making it a versatile tool for researchers and site managers to analyze microclimate conditions and trends relevant to CH preservation.

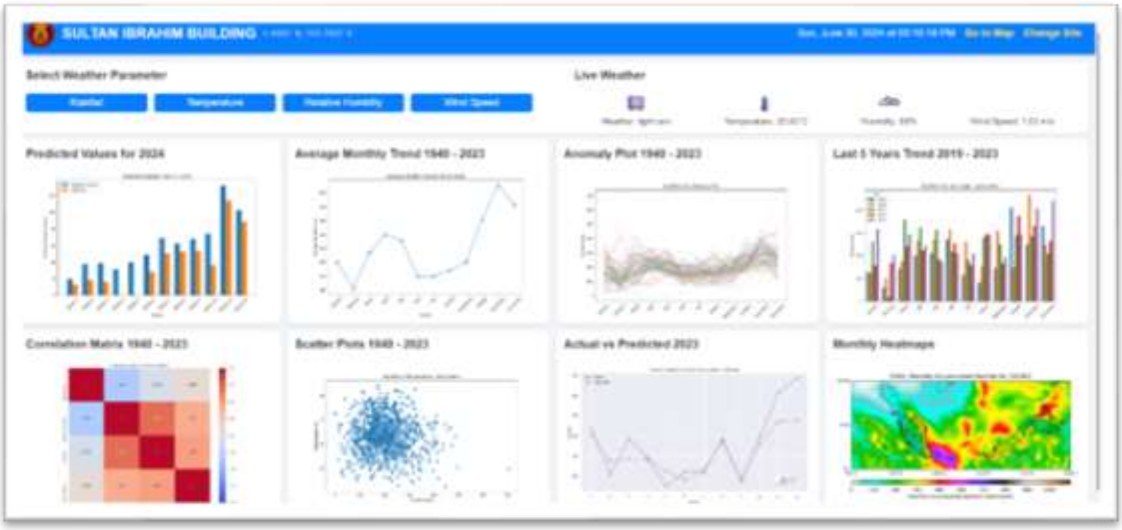

Figure 21: Johor Bahru Dashboard

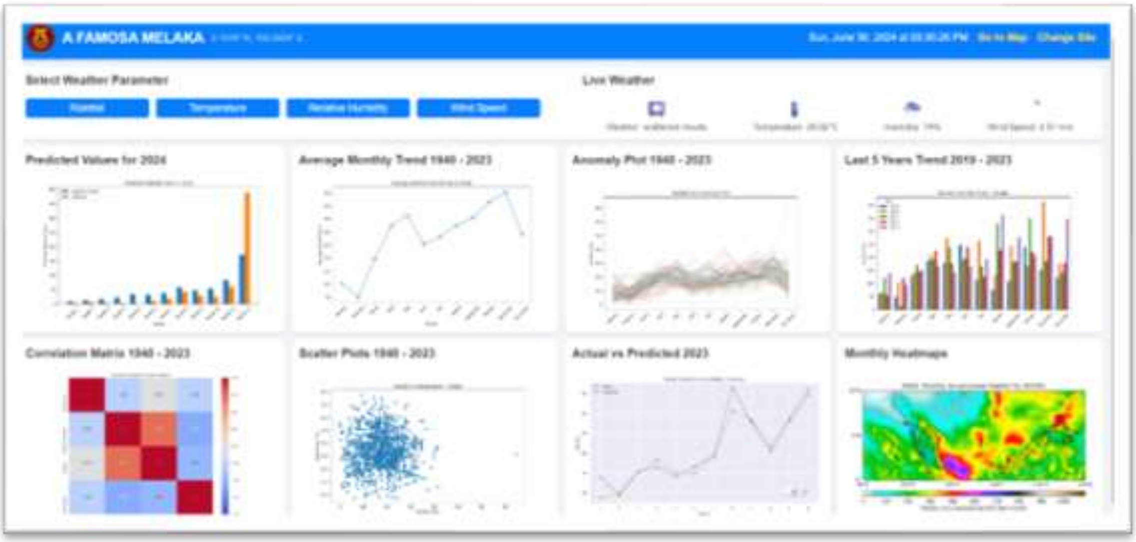

Figure 22: Melaka Dashboard

CHAPTER 5

RESULT AND DISCUSSION

5.1 Analysis of Result

The microclimate predictions for Johor Bahru and Melaka in 2023 using RF 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. Figure 23 presents wind speed predictions for Johor Bahru and Melaka in 2023, comparing RF and XGBoost models.

The first graph on the top left illustrates the wind speed predictions for 2023 in Johor Bahru using the RF algorithm. The blue line represents the actual wind speed data, while the red dashed line represents the predicted wind speed. The predictions closely follow the actual data trends, although some deviations are present. The evaluation metrics for this model are 0.28 for MAE, 0.34 for RMSE, and 0.62 for R^2, indicating a reasonably good fit.

The next graph on the top right displays the wind speed predictions for 2023 in Johor Bahru using the XGBoost algorithm. In this case, the XGBoost model performs better than the RF model, with predictions more closely aligned with the actual data. The evaluation metrics are MAE of 0.27, RMSE of 0.31, and R^2 value of 0.70, indicating higher accuracy compared to the RF model.

The bottom left graph presents the wind speed predictions for 2023 in Melaka using the RF algorithm. The RF model shows some discrepancies, especially in certain months, but overall, it captures the general trend of the data. The evaluation metrics for this model are MAE of 0.19, RMSE of 0.25, and an R^2 value of 0.48, indicating a moderate fit.

The bottom right graph illustrates the wind speed predictions for 2023 in Melaka using the XGBoost algorithm. The XGBoost model performs exceptionally well, with predictions closely matching the actual data for most of the months. The evaluation metrics for this model are MAE of 0.10, RMSE of 0.18, and an R^2 value of 0.73, indicating very high accuracy. In conclusion, both RF and XGBoost models were effective in predicting wind speed for 2023, with XGBoost consistently outperforming RF in terms of accuracy.

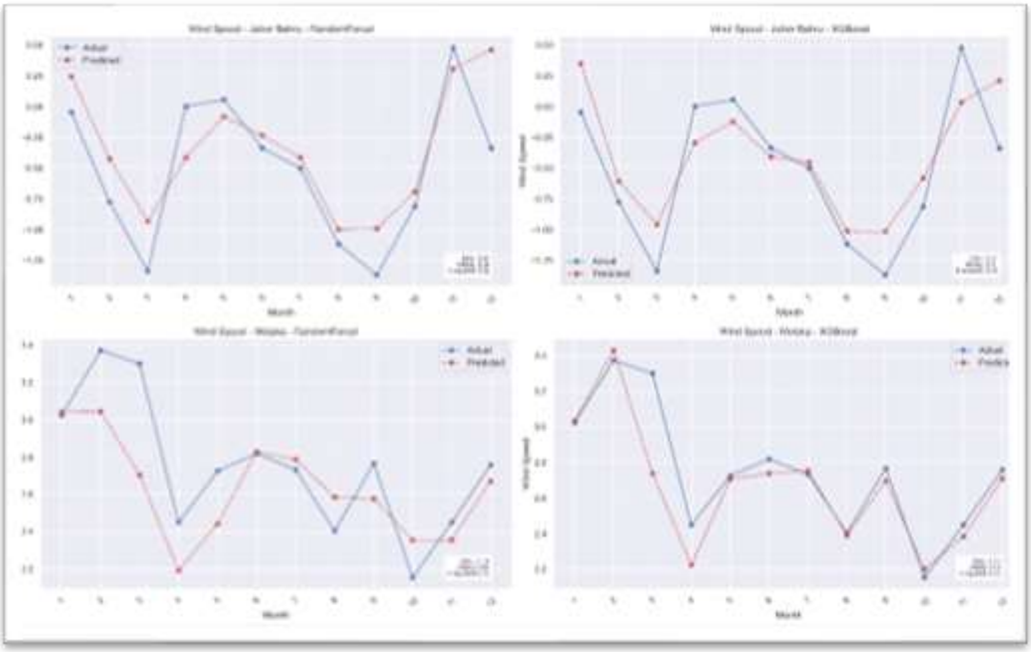

Figure 23: Wind Speed Prediction for 2023

Figure 24 illustrates the temperature predictions for 2023 using RF and XGBoost algorithms for Johor Bahru and Melaka. The top-left graph shows temperature predictions for Johor Bahru using RF. The blue line represents actual temperatures, while the red dashed line shows predictions. The model captures the overall trend well but slightly underestimates peak temperatures in mid-year. The model's performance metrics are MAE of 0.24, RMSE of 0.34, and R^2 value of 0.77, indicating good accuracy.

The top-right graph displays XGBoost predictions for Johor Bahru. This model appears to perform slightly better, especially in capturing mid-year temperature peaks. The metrics show: MAE of 0.20, RMSE of 0.26, and an R^2 value of 0.87, suggesting higher accuracy than the RF model.

The bottom-left graph shows RF predictions for Melaka. The model follows the general trend but misses some extreme temperatures, particularly the mid-year peak. The performance metrics are MAE of 0.21, RMSE of 0.33, and R^2 value of 0.74, indicating good overall performance.

The bottom-right graph presents XGBoost predictions for Melaka. This model seems to capture temperature variations more accurately, especially during mid-year peaks. The metrics show: MAE of 0.23, RMSE of 0.33, and R^2 value of 0.74, suggesting slightly better performance than the RF model.

In conclusion, both algorithms perform well in predicting temperatures, with XGBoost showing a slight edge in accuracy for both locations. The models struggle somewhat with extreme temperature events, particularly mid-year peaks, but overall provide reliable predictions.

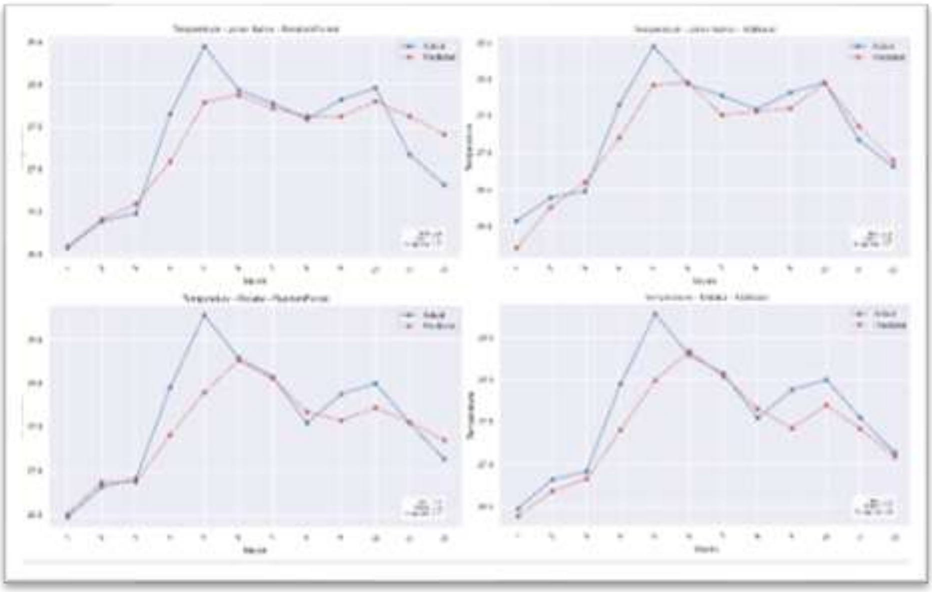

Figure 24: Temperature Prediction for 2023

Figure 25 depicts the analysis of humidity predictions for 2023 using RF and XGBoost algorithms in Johor Bahru and Melaka. Beginning with Johor Bahru, the top-left graph depicts RF predictions of humidity. Here, the blue line represents actual humidity levels, while the red dashed line denotes the model's predictions. The RF model captures the overall humidity trend adequately but encounters difficulty with extreme fluctuations, notably a sharp increase towards the end of the year. Its performance metrics reflect this with MAE of 0.75, RMSE of 0.92, and R^2 value of 0.72, indicating moderate accuracy.

Turning to XGBoost predictions for Johor Bahru in the top-right graph, this model demonstrates improved performance, particularly in capturing mid-year humidity patterns more accurately than RF. However, it also underestimates the sharp increase in humidity towards year-end. The metrics for XGBoost show an MAE of 0.49, RMSE of 0.59, and R^2 value of 0.89, suggesting higher accuracy compared to the RF model.

In Melaka, as shown in the bottom-left graph, the RF predictions generally follow the humidity trend but miss some extreme fluctuations, especially notable during mid-year periods. Despite these deviations, the model performs reasonably well with MAE of 0.70, RMSE of 0.94, and R^2 of 0.84, indicating good overall accuracy.

Examining XGBoost predictions for Melaka in the bottom-right graph, this model appears to capture humidity variations more accurately, particularly during mid-year fluctuations. Similar to Johor Bahru, it also underestimates the sharp increase in humidity towards the end of the year. However, it outperforms the RF model with metrics showing an MAE of 0.64, RMSE of 0.80, and an R^2 value of 0.88, indicating better overall performance.

In conclusion, both RF and XGBoost algorithms demonstrate reasonable effectiveness in predicting humidity for Johor Bahru and Melaka in 2023. XGBoost consistently shows better accuracy across both locations, particularly in capturing mid-year humidity patterns. Nevertheless, both models struggle with extreme humidity events, especially sharp increases towards the end of the year, suggesting potential areas for improvement in future iterations of the models.

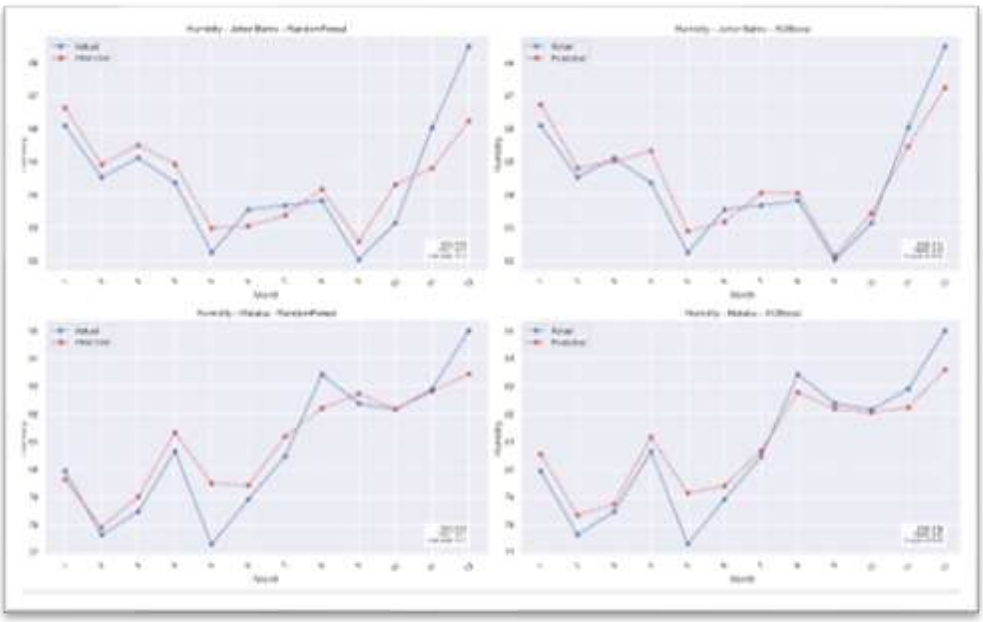

Figure 25: Humidity Prediction for 2023

Figure 26 shows analysis of rainfall predictions for 2023 using RF and XGBoost algorithms in Johor Bahru and Melaka. Beginning with Johor Bahru, the top-left graph illustrates RF predictions of rainfall. Here, the blue line represents actual rainfall amounts observed, while the red dashed line represents the model's predictions. The RF model captures the overall rainfall trend but notably underestimates extreme rainfall events, particularly evident in the last quarter of the year. Its performance metrics reflect this with a MAE of 33.23, RMSE of 48.82, and R^2 value of 0.64, indicating moderate accuracy.

Turning to XGBoost predictions for Johor Bahru in the top-right graph, this model performs similarly to RF, capturing general rainfall trends but also underestimating extreme rainfall events. However, it shows slight improvement over RF with metrics showing an MAE of 31.40, RMSE of 43.25, and an R^2 value of 0.72, suggesting slightly better performance.

Shifting focus to Melaka in the bottom-left graph, the RF predictions follow the general rainfall trend but struggle with extreme events, particularly underestimating high rainfall occurrences in August and December. Despite these challenges, the model performs reasonably well with metrics of MAE 25.89, RMSE 35.86, and an R^2 value of 0.81, indicating good overall performance.

Examining XGBoost predictions for Melaka in the bottom-right graph, this model appears to capture rainfall variations more accurately, especially during mid-year fluctuations. However, it also underestimates extreme rainfall in August. Nevertheless, it significantly outperforms the RF model with metrics showing an MAE of 16.90, RMSE of 24.66, and an R^2 value of 0.91, indicating substantially better performance.

In conclusion, both RF and XGBoost algorithms face challenges in accurately predicting extreme rainfall events, which are critical in rainfall forecasting. XGBoost generally exhibits better performance than RF, particularly highlighted in Melaka. The models' difficulty with extreme events underscores the need for further refinement, potentially through the incorporation of additional features or the use of specialized models tailored for extreme event prediction.

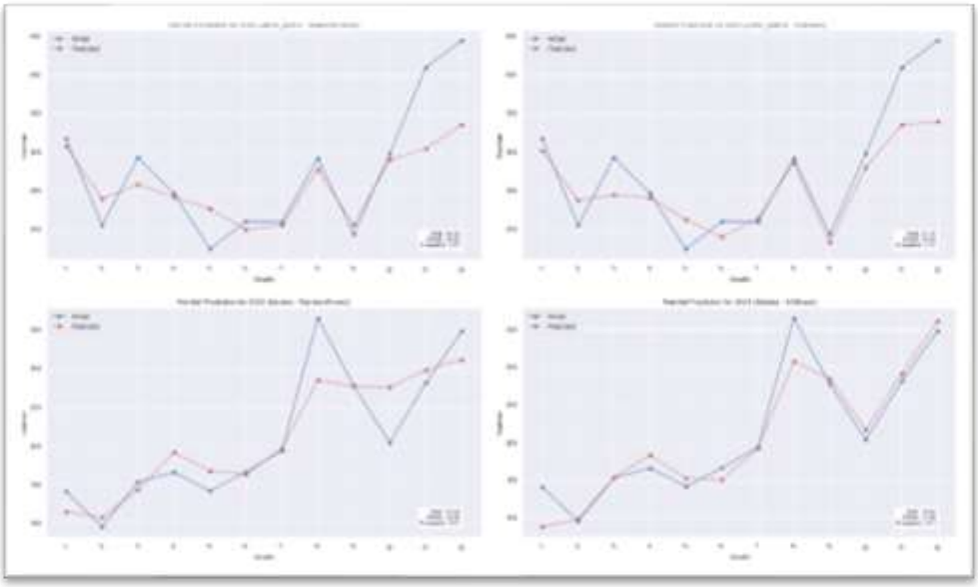

Figure 26: Rainfall Prediction for 2023

5.2 Justification of using of Log Transformation in Rainfall Prediction

In our rainfall prediction analysis, we encountered a common characteristic of rainfall measurements: positive skewness. This distribution is typified by a concentration of data points at the lower end of the scale, representing frequent occurrences of little to no rainfall, coupled with fewer but extremely high values that significantly extend the distribution's right tail. Such a pattern is intrinsic to rainfall data due to the nature of precipitation events, where numerous days may see minimal rainfall, while occasional heavy downpours result in substantially larger measurements. This skewness poses challenges for statistical analyses, as it can disproportionately influence measures like the mean, rendering them less representative of typical conditions. Moreover, many statistical techniques and machine learning algorithms assume normally distributed data, which positively skewed distributions violate.

To address these issues and enhance the robustness of our analysis, we employed a log transformation on the rainfall data. This mathematical operation helps to "normalize" the distribution by compressing the scale of higher values while expanding that of lower values. Consequently, it mitigates the impact of extreme events and allows our models to better handle the wide range between minimal and substantial rainfall amounts. The log transformation is particularly beneficial for rainfall data as it preserves the relative differences in precipitation levels while making the distribution more symmetrical and amenable to statistical analysis. By implementing this transformation, we aim to improve the accuracy and reliability of our climate predictions, ensuring that our models can effectively capture both the frequent low-rainfall periods and the less common but significant heavy precipitation events.

Figure 27 below shows the rainfall prediction after the log transformation is implemented. The first graph on the top left illustrates the rainfall predictions for 2023 in Johor Bahru using the RF algorithm. The predictions closely follow the actual data trends, although some deviations are present. The evaluation metrics for this model are 1.495 for MAE, 4.126 for RMSE, and 0.997 for R^2, indicating better result rather than before implementing the log transformation.

The next graph on the top right displays the rainfall predictions for 2023 in Johor Bahru using the XGBoost algorithm. In this case, the XGBoost model performs worser than the RF model. The evaluation metrics are MAE of 10.582, RMSE of 17.821, and R^2 value of 0.952, indicating that after log transformation, the algorithm also cannot give good value for MAE and RMSE.

The bottom left graph presents the wind speed predictions for 2023 in Melaka using the RF algorithm. The RF model shows some discrepancies, especially in certain months, but overall, it captures the general trend of the data. The evaluation metrics for this model are MAE of 0.873, RMSE of 2.127, and an R^2 value of 0.999, indicating a moderate fit.

The bottom right graph illustrates the wind speed predictions for 2023 in Melaka using the XGBoost algorithm. The XGBoost model performs with predictions closely matching the actual data for most of the months. The evaluation metrics for this model are MAE of 1.416, RMSE of 2.556, and an R^2 value of 0.999, indicating very high accuracy. In conclusion, both RF and XGBoost models for rainfall prediction were more accurate after implementing the log transformation.

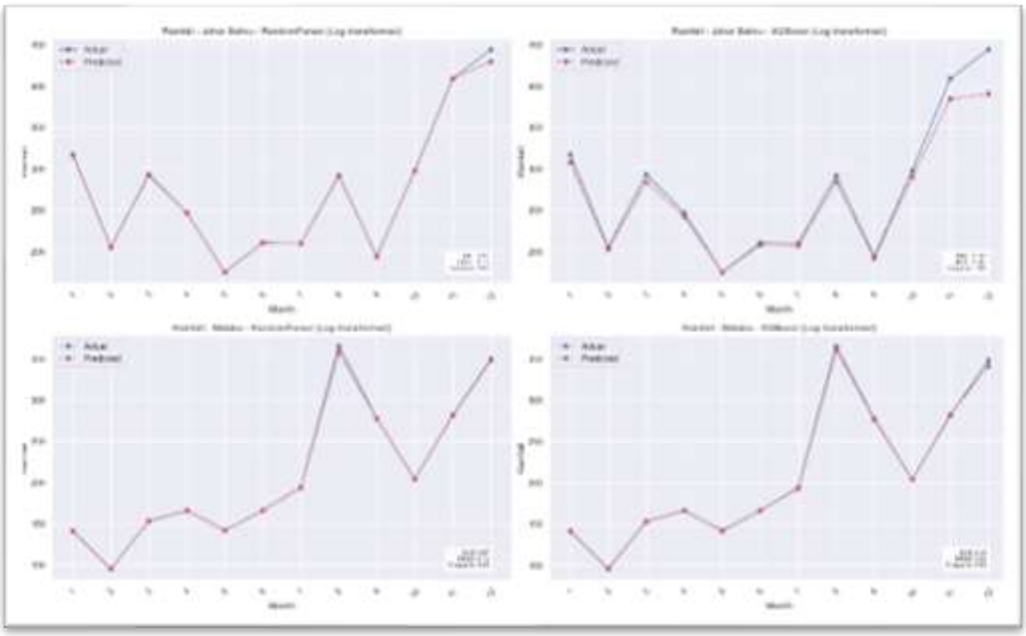

Figure 27: Rainfall Prediction for 2023 (Log Transformed)

5.3 Evaluation of Accuracy

In Johor Bahru, the RF and XGBoost models exhibited varied performance across different microclimate variables. For humidity prediction, XGBoost demonstrated superior accuracy compared to RF. The R^2 values also favored XGBoost, indicating a better fit for the data. Temperature predictions were more successful for both models, with low MAE and RMSE values indicating precise forecasting abilities. Wind speed predictions showed moderate performance, with both models achieving reasonable MAE and RMSE values. In contrast, both models struggled with rainfall prediction, showing higher MAE and RMSE value and lower R^2 values, suggesting challenges in capturing the variability of rainfall patterns accurately even after implementing log transformation.

Figure 28: Accuracy Results Table - Johor Bahru

In Melaka, XGBoost consistently outperformed RF across most metrics. XGBoost showed lower MAE values for humidity, temperature, and wind speed predictions compared to RF. However, there were indications of potential issues in datasets for rainfall predictions, as suggested by high MAE and RMSE values for XGBoost and RF. Overall, both models demonstrated the potential of machine learning in accurately predicting microclimate variables.

Figure 29: Accuracy Results Table - Melaka

5.4 Application of Prediction Results for Cultural Heritage Preservation

The prediction results from the RF and XGBoost models offer valuable insights that can significantly aid in the preservation of cultural heritage sites in Johor Bahru and Melaka. These models' accurate forecasting of microclimate variables such as wind speed, temperature, humidity, and rainfall is crucial for developing effective conservation strategies.

Accurate wind speed predictions help in assessing the potential structural stress on heritage buildings, particularly those with intricate architectural elements. High wind speeds can cause physical damage to roofs, walls, and exposed decorative features. By using the predicted wind speed data, heritage site managers can schedule regular maintenance and reinforce structural elements to withstand predicted high winds. Additionally, in the event of forecasted strong winds, temporary protective measures such as bracing or covering vulnerable structures can be implemented to prevent damage.

Temperature predictions are essential for managing the thermal stress that can affect building materials over time. Variations in temperature can cause expansion and contraction in materials like wood, stone, and metal, leading to cracks and other forms of degradation. Installing and optimizing climate control systems within indoor heritage sites can help mitigate the effects of extreme temperature fluctuations. Temperature data can also guide the choice of preservation materials and techniques that are more resilient to thermal stress.

Humidity levels play a critical role in the preservation of both the structural integrity and the artifacts within heritage sites. High humidity can promote mold growth, corrosion, and decay of organic materials, while low humidity can cause desiccation and cracking. Implementing humidity control measures, such as dehumidifiers or humidifiers, can help maintain stable indoor environments that protect sensitive materials. Regular monitoring and adjustment of humidity levels can prevent long-term damage to both the buildings and their contents.

Rainfall data is crucial for planning and maintaining the drainage systems around heritage sites to prevent water accumulation, which can lead to structural damage and erosion. Enhancing waterproofing measures, such as installing effective guttering and drainage systems, can protect buildings from water damage. Managing the surrounding landscape to ensure proper drainage can prevent waterlogging and soil erosion, preserving the structural foundations of heritage buildings.

Integrating these predictive models into the management plans for cultural heritage sites enables proactive and informed decision-making. By leveraging the accurate microclimate predictions provided by the RF and XGBoost models, heritage conservationists can implement timely interventions and maintenance activities that ensure the long-term preservation of these invaluable sites. This approach not only enhances the resilience of heritage structures against climatic stressors but also contributes to the sustainable management of cultural heritage in Johor Bahru and Melaka.To conclude, the slightly better performance of XGBoost compared to RF algorithms suggests that the limitation may partially lie in the features used for prediction rather than solely in the choice of algorithm. However, both models exhibit challenges in accurately predicting extreme events, particularly in rainfall, indicating a need for additional relevant features or a different approach to handling highly variable weather phenomena. In conclusion, while both models demonstrate predictive capability for humidity, they face significant difficulties in rainfall prediction. The elevated MAE and RMSE values underscore the complexity of weather prediction, especially concerning highly variable factors like rainfall. Future research could focus on integrating additional relevant features, exploring more advanced time series models, or leveraging ensemble methods that might better capture the intricate patterns in weather data.

5.5 Chapter Summary

To conclude, the slightly better performance of XGBoost compared to RF algorithms suggests that the limitation may partially lie in the features used for prediction rather than solely in the choice of algorithm. However, both models exhibit challenges in accurately predicting extreme events, particularly in rainfall, indicating a need for additional relevant features or a different approach to handling highly variable weather phenomena. In conclusion, while both models demonstrate predictive capability for humidity, they face significant difficulties in rainfall prediction. The elevated MAE and RMSE values underscore the complexity of weather prediction, especially concerning highly variable factors like rainfall. Future research could focus on integrating additional relevant features, exploring more advanced time series models, or leveraging ensemble methods that might better capture the intricate patterns in weather data.

CHAPTER 6

CONCLUSION

6.1 Research Outcomes

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

One of the key research outcomes is the development of microclimate prediction utilizing the RF and XGBoost algorithms. The system collects data from Copernicus CDS, including temperature, humidity, rainfall and wind speed. The collected data is then processed and analyzed using the RF 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 CH sites. By training the RF 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.

6.2 Contributions to Knowledge

The research conducted in this thesis has made several contributions to the field of CH preservation and microclimate monitoring. These contributions include the application of machine learning algorithms, specifically the RF and XGBoost algorithms, in the context of microclimate monitoring and prediction at CH 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 CH sites. This framework integrates data collection, preprocessing, analysis, and prediction using the RF and XGBoost algorithms. The developed framework can serve as a guide for future researchers and practitioners in the field of CH 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 CH 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.

6.3 Research Limitations

Despite the positive outcomes, this research has several limitations. One of the primary limitations is the use of monthly data instead of daily or hourly data. Utilizing more granular data could potentially improve the accuracy and reliability of the predictions. However, the available data for 2024 is incomplete, as data from January to December is still not available, which is why this research focuses on predicting 2023 data and comparing it with the actual data for that year.

Another limitation is related to hardware constraints. Due to limited computational resources, the study was conducted at only two locations. Expanding the study to include more locations would likely provide a more comprehensive understanding of microclimate variations but would also require significantly more computational power and time to process the data.

6.4 Future Works

While this research has achieved significant milestones in the preservation of CH 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 CH 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 CH 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 CH preservation can continue to evolve and contribute to the sustainable management of these invaluable cultural assets.

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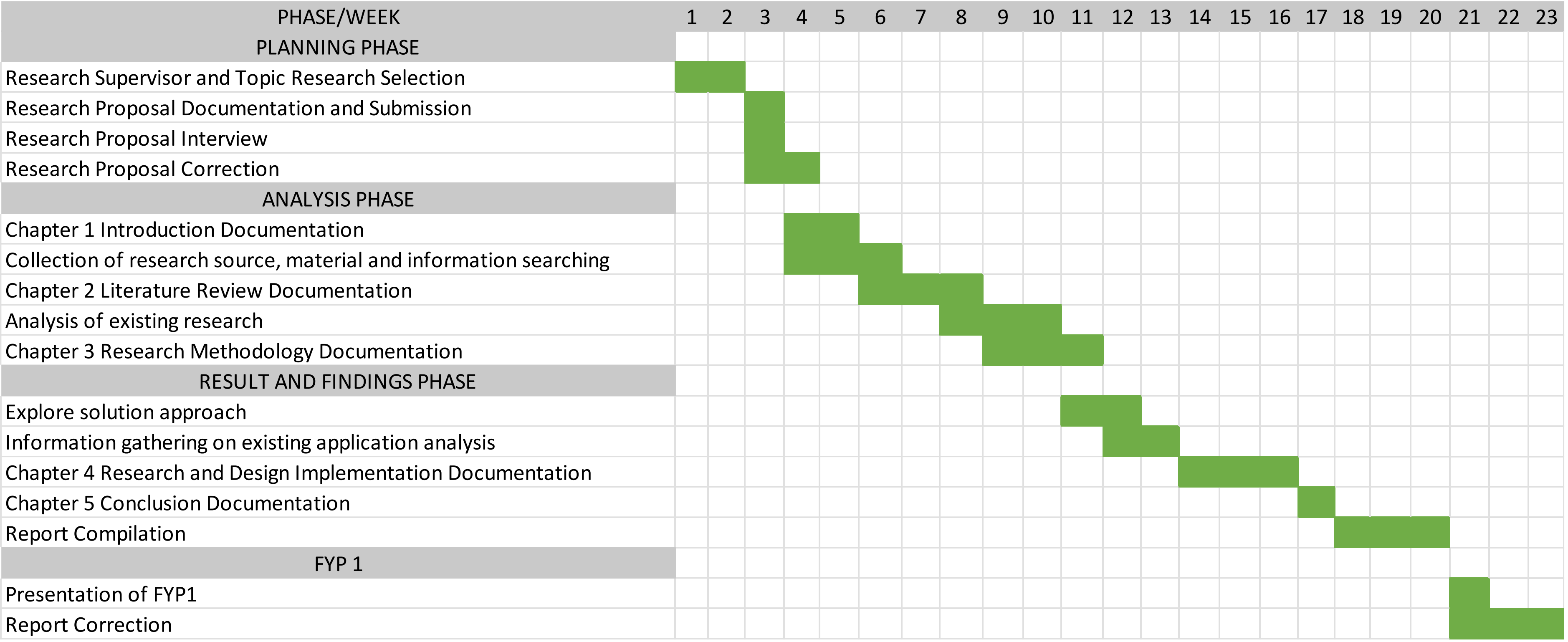
APPENDIX A: Gantt Chart for FYP 1



APPENDIX B: Gantt Chart for FYP 2