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Faculty of Information Technology
Department of Information Systems

PREDICTING HURRICANE INTENSITY AND TRAJECTORIES

USING MACHINE LEARNING AND SATELLITE DATA

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Content of the coursework

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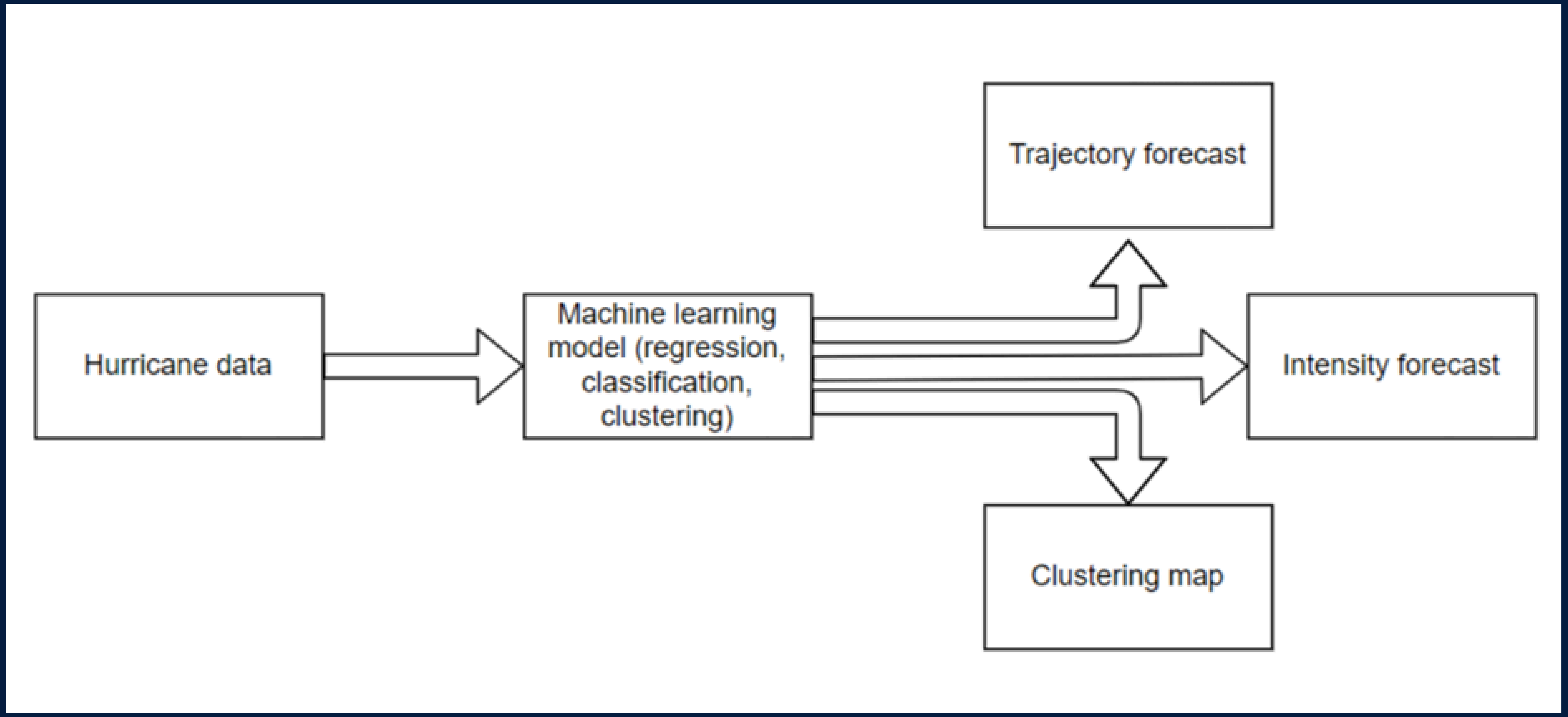
Introduction

Hurricanes represent one of the most devastating natural phenomena, causing widespread destruction to lives, infrastructure, and economies. Predicting their intensity and trajectories is crucial for effective disaster management, early warning systems, and mitigating potential damages. Despite significant advancements in meteorology and weather forecasting, the complex and nonlinear dynamics of hurricanes present a formidable challenge for precise predictions. This project addresses these challenges by leveraging modern machine learning techniques and satellite data to enhance our ability to forecast hurricane behavior.

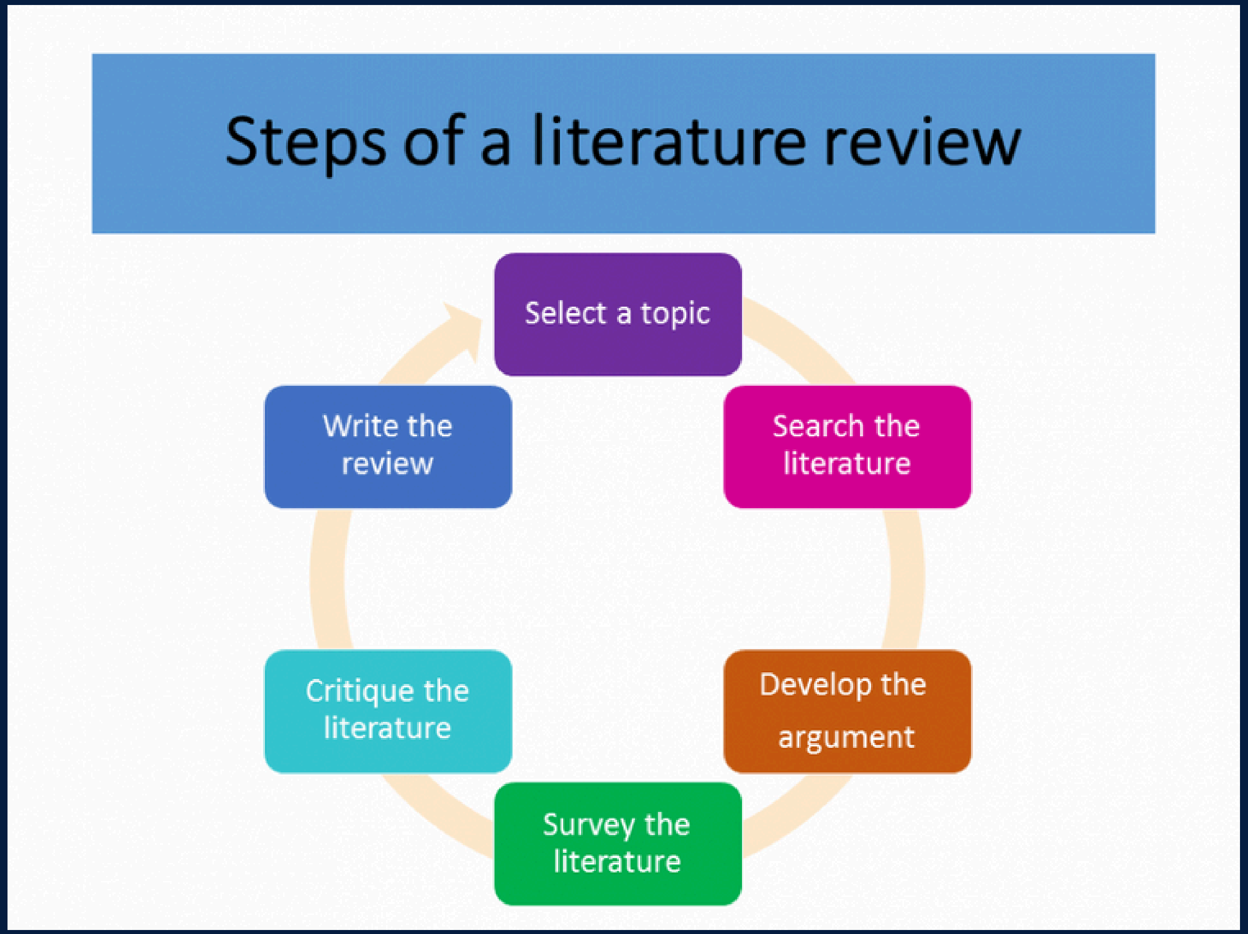
The diagram below illustrates the workflow of the project, where hurricane data is processed through machine learning models to generate trajectory forecasts, intensity forecasts, and clustering maps. This approach combines predictive analytics with real-world applications, showcasing the integration of artificial intelligence in meteorology.



Literature review

This literature review examines advancements in machine learning and statistical approaches relevant to predicting hurricane intensity and trajectories. By analyzing key methodologies and frameworks, the review establishes a foundation for understanding how machine learning can address the complexities of meteorological forecasting. The discussion also identifies the project's contribution to this evolving field.

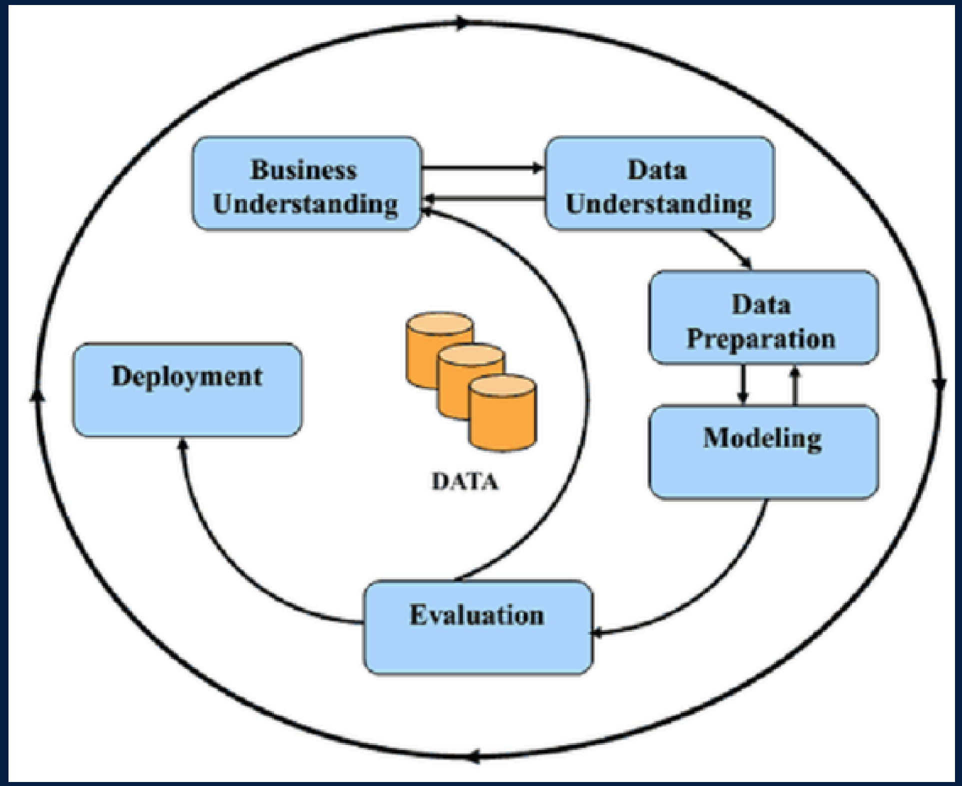
Machine learning, a branch of artificial intelligence, offers data-driven solutions for complex tasks, including hurricane prediction. Unlike physics-based models that rely on explicit equations, machine learning identifies patterns in historical data to make predictions. This approach has proven particularly valuable for nonlinear problems, such as forecasting hurricane intensity and trajectories, where traditional methods may struggle due to the chaotic nature of weather systems.



Project methodology

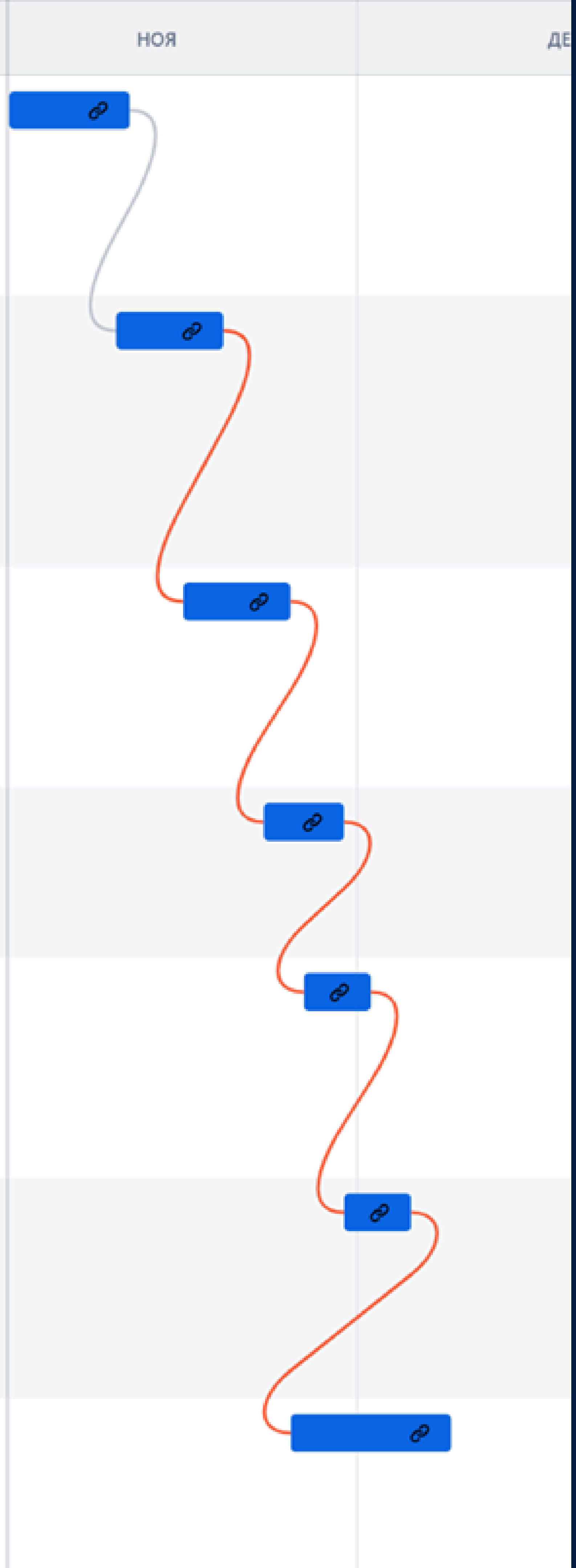
The methodology for project “Predicting hurricane intensity and trajectories using machine learning and satellite data” follows the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework, a well-established approach widely used in data mining and machine learning projects. CRISP-DM offers a systematic and structured method, ensuring that all necessary stages are covered while allowing the project to proceed efficiently. This approach was chosen for its flexibility and adaptability, especially in complex projects such as predicting hurricane behavior using satellite data, which involves handling large amounts of diverse data and building robust predictive models.

Project planning is a critical component of any successful project, as it ensures that tasks are well-defined and organized, and that resources and timelines are allocated effectively. In this project, I used the Jira platform to break down tasks, establish timelines, and monitor progress. This structured approach helped mitigate risks, ensured efficient resource allocation, and kept the project on track.



No.	Main Task	Subtasks	Start Date	End Date
1	Preparatory Stage	Study hurricane prediction methods, define database structure, select tools	05.11.2024	13.11.2024
2	Data Collection and Preprocessing	Collect data, preprocess and clean	13.11.2024	20.11.2024
3	Authorization and Registration	Develop user registration page, data validation	18.11.2024	25.11.2024
4	Development of Flowcharts and UML Diagrams	Create flowcharts, build UML diagrams	24.11.2024	29.11.2024
5	Implementation of the Machine Learning Model	Develop RNN (LSTM) for trajectory, CNN/regression for intensity	27.11.2024	01.12.2024
6	Model Evaluation	Visualize results, evaluate performance	30.11.2024	04.12.2024
7	Documentation	Write report with project details and results	26.11.2024	04.12.2024
8	Final Testing and Wrap-up	Final testing,	05.12.2024	07.12.2024

~~KAN-2~~	Preparatory sta...	ГОТОВО
~~KAN-3~~	To study the subject area: hurricane prediction methods and satellite data analysi...	ГОТОВО
~~KAN-4~~	Define the database structure and dataset form...	ГОТОВО
~~KAN-5~~	Select tools for authorization and registration.	ГОТОВО
~~KAN-6~~	Database connection and dataset downlo...	ГОТОВО
~~KAN-7~~	Develop a database structure for storing hurricane dat...	ГОТОВО
~~KAN-8~~	Columns: date, coordinates, intensity, pressure, wind spee...	ГОТОВО
~~KAN-9~~	Implement a database connectio...	ГОТОВО
~~KAN-10~~	Upload and clear data	ГОТОВО
~~KAN-11~~	Authorization and registration pa...	ГОТОВО
~~KAN-12~~	Implement a user registration module.	ГОТОВО
~~KAN-13~~	Data validation (e.g., email, password).	ГОТОВО
~~KAN-14~~	Restrict access to data for unauthorized users.	ГОТОВО
~~KAN-15~~	Development of flowcharts and UML diagra...	ГОТОВО
~~KAN-16~~	Build a flowchart of the model	ГОТОВО
~~KAN-17~~	Create UML diagra...	ГОТОВО
~~KAN-18~~	Implementation of the machine learning mod...	ГОТОВО
~~KAN-19~~	Develop and train models: RNN (for example, LSTM) for trajectories. CNN or regression model for intensity.	ГОТОВО
~~KAN-20~~	Integrate the model into the API: Endpoints for sending data and receiving predictio...	ГОТОВО
~~KAN-21~~	Visualize the results: Graphs of trajectories and intensities.(based on logistic regression, decision tree))	ГОТОВО
~~KAN-22~~	Video (1 minute)	ГОТОВО
~~KAN-23~~	Write a video script: An introduction to the project. Demonstration of the interface or API. Examples of how the...	ГОТОВО
~~KAN-24~~	Record and edit the vide...	ГОТОВО
~~KAN-25~~	Make sure that the video meets the requirements (no more than 1 minut...	ГОТОВО
~~KAN-26~~	Documentation (report)	ГОТОВО
~~KAN-27~~	Write a structured report: Introduction. Methods and architecture. Description of the models. The test results....	ГОТОВО
~~KAN-28~~	Add links to diagrams, code, and video...	ГОТОВО



Dataset

Datasets are the cornerstone of machine learning, as they provide the raw information needed to train, validate, and test predictive models. The quality, diversity, and structure of the data significantly impact the performance and reliability of the model. For tasks related to hurricane analysis and prediction, datasets enable researchers to uncover patterns in meteorological conditions, measure cyclone intensity, and predict the trajectory or category of storms.

In this project, the dataset focuses on hurricanes, capturing critical atmospheric and oceanographic features over time. It aims to assist in developing a predictive model that can classify the cyclone category based on environmental and oceanic parameters.

The dataset used in this project was sourced from the National Oceanic and Atmospheric Administration (NOAA). NOAA provides publicly accessible and reliable data related to weather, climate, and oceanic phenomena. The hurricane-related dataset was extracted from NOAA's archives, which include historical storm tracks, atmospheric conditions, and oceanic measurements.

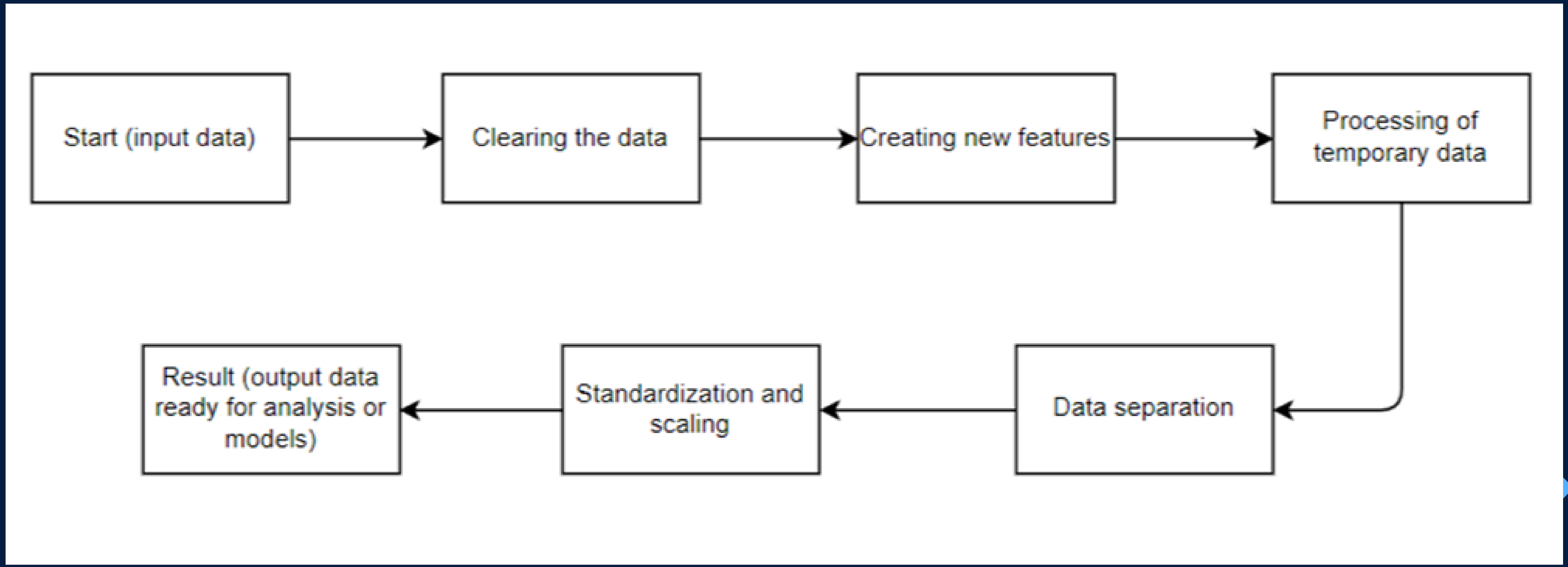
The dataset includes the following features:

Feature	Description
Timestamp	The date and time of the observation.
Atmospheric Pressure (hPa)	The pressure exerted by the atmosphere at the time of observation, measured in hectopascals.
Air Temperature (°C)	The air temperature at the observation point.
Humidity (%)	The percentage of atmospheric moisture.
Wind Speed (km/h)	The speed of the wind, measured in kilometers per hour.
Precipitation (mm)	The total rainfall or precipitation in millimeters.
Sea Surface Temperature (°C)	The temperature of the sea surface at the observation location.
Ocean Heat Content (J)	The energy stored in the ocean, measured in joules.
Wave Height (m)	The height of the waves at the observation point.
Lightning Frequency (Hz)	The frequency of lightning strikes, measured in hertz.
Longitude	The geographic coordinate specifying the east-west position.
Latitude	The geographic coordinate specifying the north-south position.
Cyclone Category	The classification of the cyclone based on its intensity (e.g., Tropical Depression, Hurricane Category 1-5).

Representation of dataset

Timestamp	AtmosphericPressure_hPa	AirTemperature_C	Humidity_%	WindSpeed_kmh	Precipitation_mm	SeaSurfaceTemperature_C	OceanHeatContent_	WaveHeight_m	LightningFrequency_H	Longitude	Latitude	CycloneCategory
04.12.2024 0:00	940.2428427411834	29.24493826026054	86.54106177867683	59.76835098135657	17.60988236810217	28.58094909431521	217948681.96861356	2.820089120798412	1.799918055283748	-82.16696893802546	18.71072758007456	Hurricane Category 1
04.12.2024 1:00	916.777993459751	34.626519149981505	70.37912747069629	174.98306178907504	126.16206446395888	30.318411384856525	407441620.86813545	4.954693422966034	5.395714123476328	-86.72806638915301	11.779145864709918	Tropical Depression
04.12.2024 2:00	962.3235337550071	31.660515424103323	98.62730113549503	189.41302517955796	69.14850812638942	28.32324473094926	266324717.11402225	2.525896033343756	7.380084511621176	-81.22964347187775	26.73638571422683	Hurricane Category 2
04.12.2024 3:00	905.3418644671548	29.79164701222152	78.41562208676979	140.45344503429592	39.55897621196558	29.446463639308913	308375919.13627243	0.86084905046789	3.45639290256631	-77.27273420035895	20.238275703460747	Hurricane Category 2
04.12.2024 4:00	946.0775722641553	29.400320671443527	60.739081403894616	193.9901512614268	74.039181817605	29.74941934953227	384942752.3117685	2.4057966405158497	6.697362268270043	-98.40139606464328	13.77453460329949	Hurricane Category 3
04.12.2024 5:00	976.8100479522236	28.36475923094929	99.94827470569534	148.9289258016148	123.55709329042625	28.188214533762878	489525392.60809183	4.830897135141489	2.5830156522377057	-78.61290250872713	19.09197122758102	Hurricane Category 4
04.12.2024 6:00	974.3842431108932	32.91838727941021	74.6623805587155	104.95550773516402	91.68464820418596	29.340584784698166	417951422.70260173	4.577405640523283	2.1671050657549107	-80.43165238939586	23.020658601490837	Hurricane Category 1
04.12.2024 7:00	944.3040192358515	26.42191924072925	76.84030083760656	67.05802087484851	91.66111198551216	27.981541772838263	194749441.27697486	3.3486617060640906	3.1807310413260224	-70.906529352137	16.710387710475725	Hurricane Category 4
04.12.2024 8:00	969.6004656915832	29.082925828450445	69.78604381092796	157.86028770796383	100.82835668538172	29.98619691006659	186752594.53781587	0.9171049568165109	8.884302355735713	-87.34455326126204	10.950659855502513	Tropical Storm
04.12.2024 9:00	988.483489812075	28.89787897840864	94.112005803036	136.5148065511769	16.024343477274595	27.884217957983644	252799557.10727987	1.0877414010722293	1.021569736579695	-82.18004439378618	23.502610861169096	Hurricane Category 3
#############	901.768626316155	34.345866793687314	73.06159993955418	90.67274485636722	27.57309179758698	30.240741801497087	181104488.06082588	4.921703217167841	3.618780914447788	-95.30234562797726	14.913228928940995	Hurricane Category 3
#############	977.9758579638814	30.27554885329325	60.349717114703196	179.07584823532926	10.851211442701313	27.747419289372676	193704883.5992774	2.3007431276437575	7.408124178946274	-69.510652848738	17.43077833192956	Tropical Storm
#############	937.5966717351798	33.68670194999815	60.502867820580974	88.03133865102534	168.2581440962273 4	26.967908639137217	154500303.92723826	1.3097785171202334	1.9275004235990068	-86.94395131100805	14.950417987008569	Hurricane Category 4
#############	925.2677414738071	29.63794193345541	97.57666466930368	182.6857652763069	174.7021306761912	27.28725977895887	147392057.9404184	1.1418884081760574	3.2760753908998366	-87.03523828907846	16.25725037908117	Tropical Storm
#############	953.5846873685356	32.43294098759295	78.59615876485653	155.40195615616142	15.322598475435756	28.311075848402766	388094598.1095131	1.0346191185962228	4.308911663048452	-86.15632022787638	21.978849853817678	Tropical Depression
#############	1009.8229783117681	34.886520270359604	75.93140365073609	195.8625477898347	143.35205877453845	27.059794131197577	241608372.49621806	3.311725014541364	3.1350101193218363	-73.31325512684558	10.411438994994649	Tropical Storm
#############	992.2544145717286	30.36389364765978	95.66046991549038	98.11479814070296	84.76160040776048	27.382372376064108	430988417.9038544	4.416505977010264	8.617092492430757	-70.79325720417278	26.06849341456549	Hurricane Category 4
#############	989.2913289055732	30.07744572193255	74.48384409824372	135.04128722767933	176.61855148148754	29.201185290791848	324180770.00112224	3.5220919007586358	2.8564579369865672	-92.66818745861474	27.981670092737605	Tropical Depression
#############	997.9140167713841	34.13318353516837	99.43940421751233	175.31075833424882	95.37870638158455	28.49989431470683	478200434.1316819	2.220733715415256	4.90472636374048	-65.2505056067522	27.186300953306652	Hurricane Category 1
#############	955.9947004494328	31.69176925628824	82.93814108481254	115.68787180117276	129.47197255546868	29.90586386142984	315100017.6470229	2.5969906742565887	6.909003681263506	-91.61739822487223	15.902458073836899	Hurricane Category 4
#############	909.4923450710952	28.94483723001367	67.07833040362347	61.5893649526065	1.9613222041687361	30.321458790482314	319116381.41675013	4.980494832406477	0.3734216159336323	-63.88887703480194	18.51222682108405	Hurricane Category 2
#############	927.4066700580646	33.230713209651235	92.82218590952203	178.5757735453709	44.339924541523516	30.031037399200404	415145962.3109885	4.980643379784192	4.00600208293317	-72.0345955925153	21.80390145681676	Hurricane Category 4
#############	998.2575905820422	31.392130820832755	98.54568729034582	107.31824575344933	125.65295622985653	29.251378137876237	472262670.3074706	1.6829738888446528	8.935115301157504	-96.31665814247076	11.600027174922198	Hurricane Category 5
#############	1010.7964103613004	32.691805880150085	78.0978349804849	112.12665399021094	18.266543465416873	30.283015659847617	369518247.6089081	0.7133724062765106	3.6678631342419776	-93.68833041180044	11.35039274350202	Tropical Storm
05.12.2024 0:00	983.1154305851245	26.45901933603109	65.53102042080077	176.22788562997533	32.53504822583457	29.309446186443413	450523563.10734373	2.306322291036747	6.114475923669649	-68.83788622588386	26.18443350946874	Hurricane Category 1
05.12.2024 1:00	933.0748534226643	30.78315684377088	81.55123543186886	88.69877854956624	96.33744349799042	26.205076122085003	171512360.40429488	1.3403227241260802	4.462523289991157	-83.96527600984362	18.851372882681915	Hurricane Category 3
05.12.2024 2:00	931.4131930447651	28.1579872998788	84.9687945228399	54.14219256102588	115.51762786244038	29.552347413589338	339078989.6432532	3.639867017280692	2.48079661697862	-62.896367007241615	18.06324542395886	Tropical Storm
05.12.2024 3:00	950.8302306372948	34.02772592056204	73.62023254167082	103.92765166307257	0.13233857599510568	28.2093155236577	377250083.60299504	1.8021055584517764	9.577646571835537	-69.84798011650275	29.338852402702003	Hurricane Category 2
05.12.2024 4:00	999.1969190858442	31.86757729087818	91.62125551235425	148.94113232089944	52.32034525903953	30.587536589938328	455966679.4492599	1.7408325153248008	8.80054078898015	-74.67937247137287	18.771812565840204	Hurricane Category 1
05.12.2024 5:00	976.712581860091	34.55863243596555	99.09903460925048	83.40756517964189	155.92763051581835	28.486812549049482	437083622.140297	2.7971321772641327	9.012497583860862	-82.70113594897023	26.863598492300383	Hurricane Category 4
05.12.2024 6:00	963.3790492127497	32.56171176349803	84.99332258342383	152.11653407350855	178.25778831162629	28.760183494136488	232775305.2050146	2.0705438210402742	4.204246970986258	-65.40081238276936	13.943373232747502	Hurricane Category 3

Data processing workflow, which consists of the following sequential steps:



Model implementation

Machine learning is a field that combines statistics, computer science, and optimization to build models that make predictions and improve over time. It involves developing algorithms that learn patterns from data and apply these to make informed decisions. In the context of hurricane prediction, supervised learning is particularly useful. Here, the algorithm is trained using labeled data, where input-output pairs are provided, and the model learns to map inputs to outputs. This approach is central for tasks like regression and classification, which are key in forecasting hurricanes.

Several machine learning algorithms are commonly used for hurricane prediction:

1. k-Nearest Neighbors (k-NN): This algorithm predicts based on the closest data points in the training set. It works well for tasks where the decision boundary is not linear, but can be computationally expensive for large datasets and requires careful feature scaling.
2. Naive Bayes: A probabilistic classifier based on Bayes' Theorem, Naive Bayes assumes feature independence and is effective for categorical data. It is fast and efficient for large datasets but assumes features are independent, which may not always be true in meteorological contexts.

3. Support Vector Machines (SVM): SVMs are used for classification by finding the hyperplane that best separates different classes. They are effective for smaller datasets and can handle non-linear relationships using kernel functions. However, they require careful tuning of parameters.

4. Random Forest: An ensemble method that constructs multiple decision trees, Random Forests are robust to noise and outliers, and they can model complex interactions between features. They are useful for hurricane prediction because they can forecast intensity, track, and landfall probability.

The choice of algorithm depends on the task (e.g., classification or regression), the nature of the data (e.g., noisy or imbalanced), and the balance between computational efficiency and model interpretability. Each algorithm has its strengths and weaknesses, and selecting the right one involves evaluating performance metrics such as accuracy, precision, recall, and F1 score.

Model implementation

To implement a machine learning model for hurricane prediction, the process involves several essential steps, including data preprocessing, feature extraction, model training, and evaluation. In this case, we use Support Vector Machine (SVM) and Random Forest, two popular machine learning algorithms, to predict the occurrence of hurricanes based on historical weather data.

To begin, we import the necessary libraries for data processing, machine learning, and evaluation. Key libraries include pandas for data manipulation, sklearn for machine learning models and metrics, and nltk for natural language processing when needed for text data handling.

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_score, classification_report
from sklearn.preprocessing import StandardScaler
```

– pandas: A powerful library for data manipulation and handling tabular data.
– numpy: For numerical operations, especially when handling large datasets.
– sklearn: Provides a wide array of machine learning algorithms and evaluation metrics.

We load the dataset containing historical hurricane data, which includes various weather parameters such as wind speed, temperature, and atmospheric pressure, as well as the label indicating whether a hurricane occurred (1 for hurricane, 0 for no hurricane).

```
df = pd.read_csv('hurricane_data.csv')
```

Machine learning model perfomance

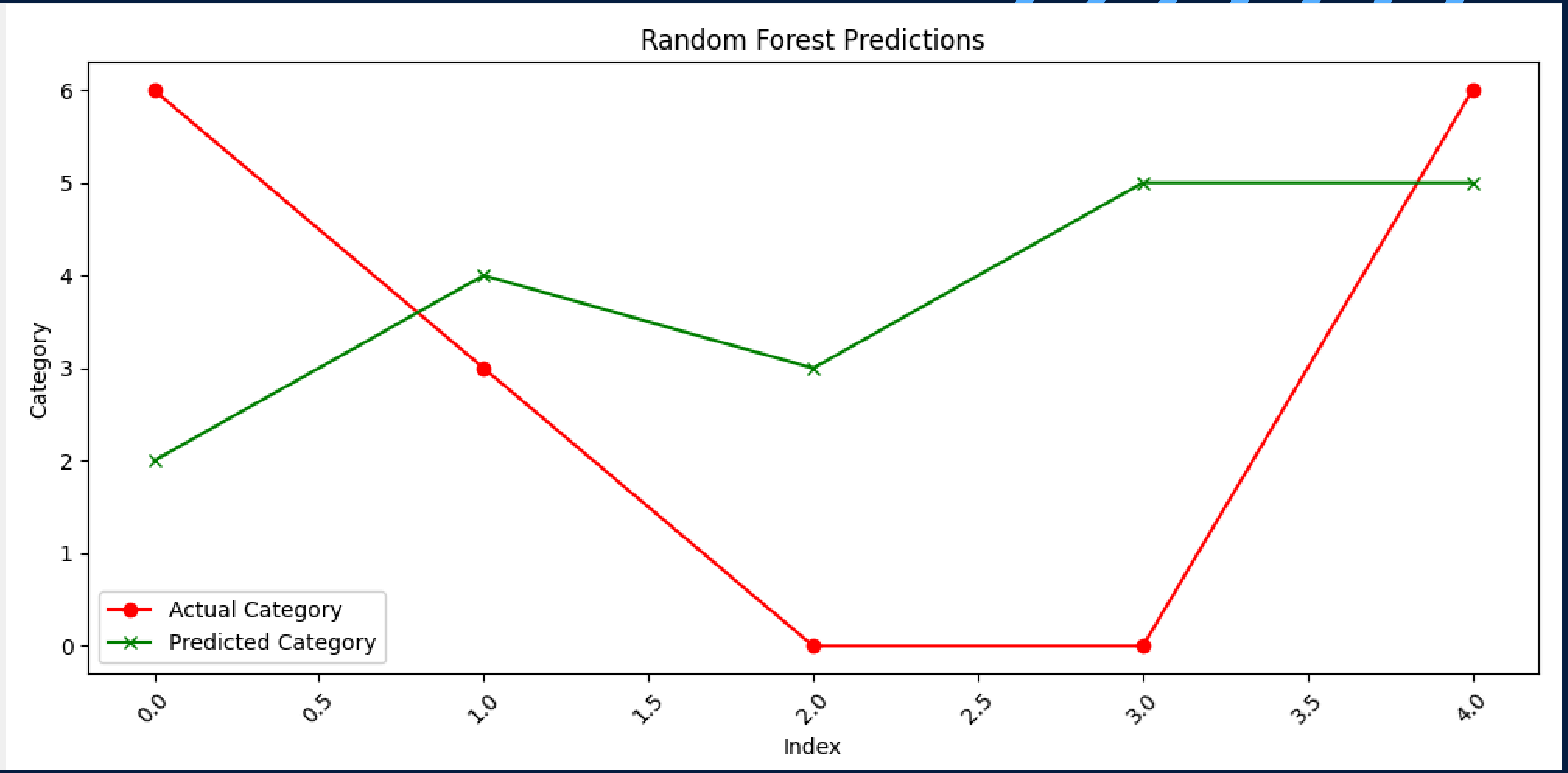
In this project, several machine learning models were used to classify hurricane categories based on features such as wind speed, atmospheric pressure, and humidity. Each model was trained and tested on a dataset, and evaluated using various metrics, including accuracy, recall, precision, and F1-score.

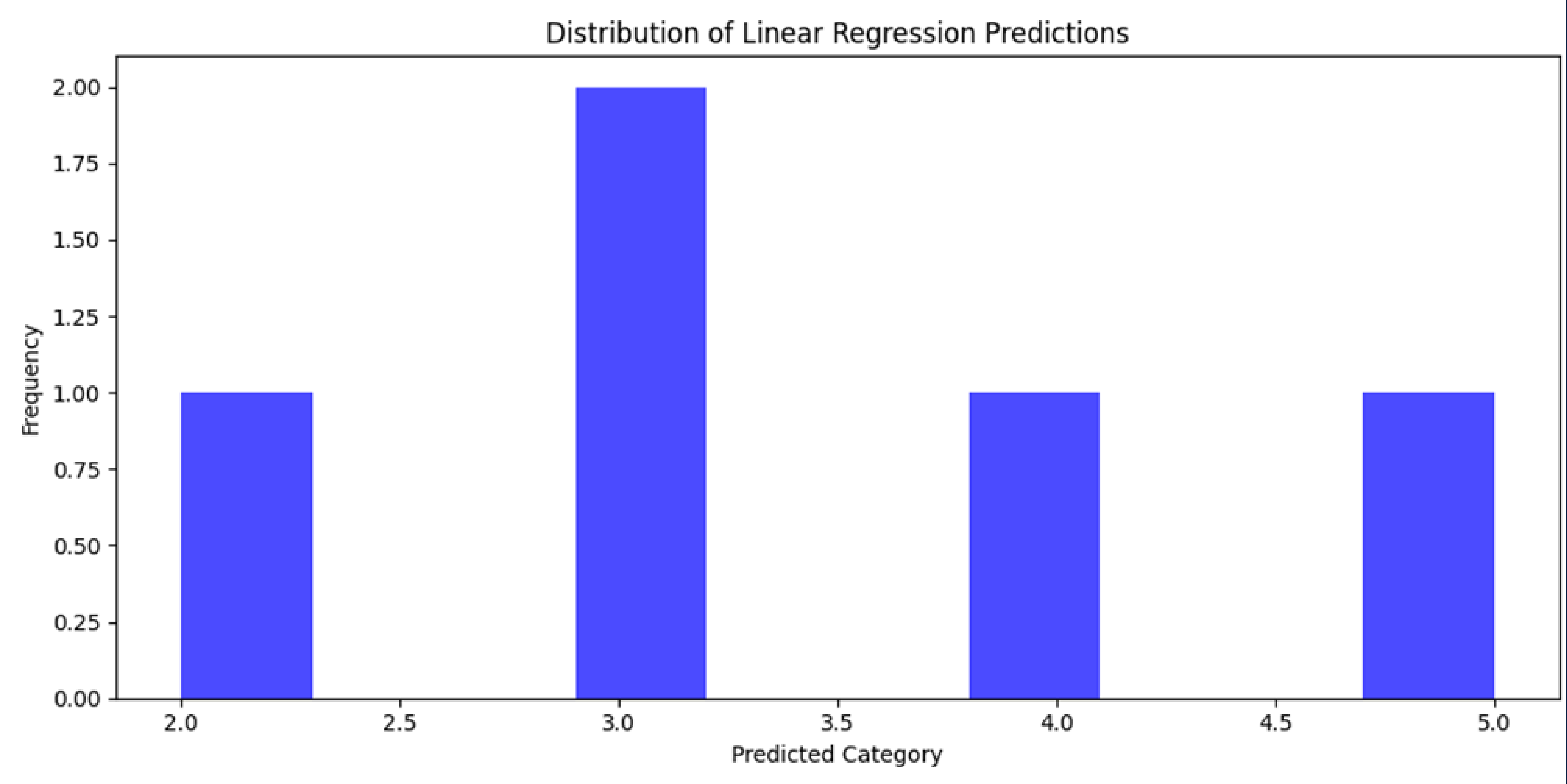
General Performance Metrics:

- Accuracy: The total proportion of correctly classified objects among all examples. In this case, the accuracy of the model is 0.12, which indicates its poor performance.
- Classification Report: Provides detailed information about metrics such as precision, recall, and f1-score for each class.

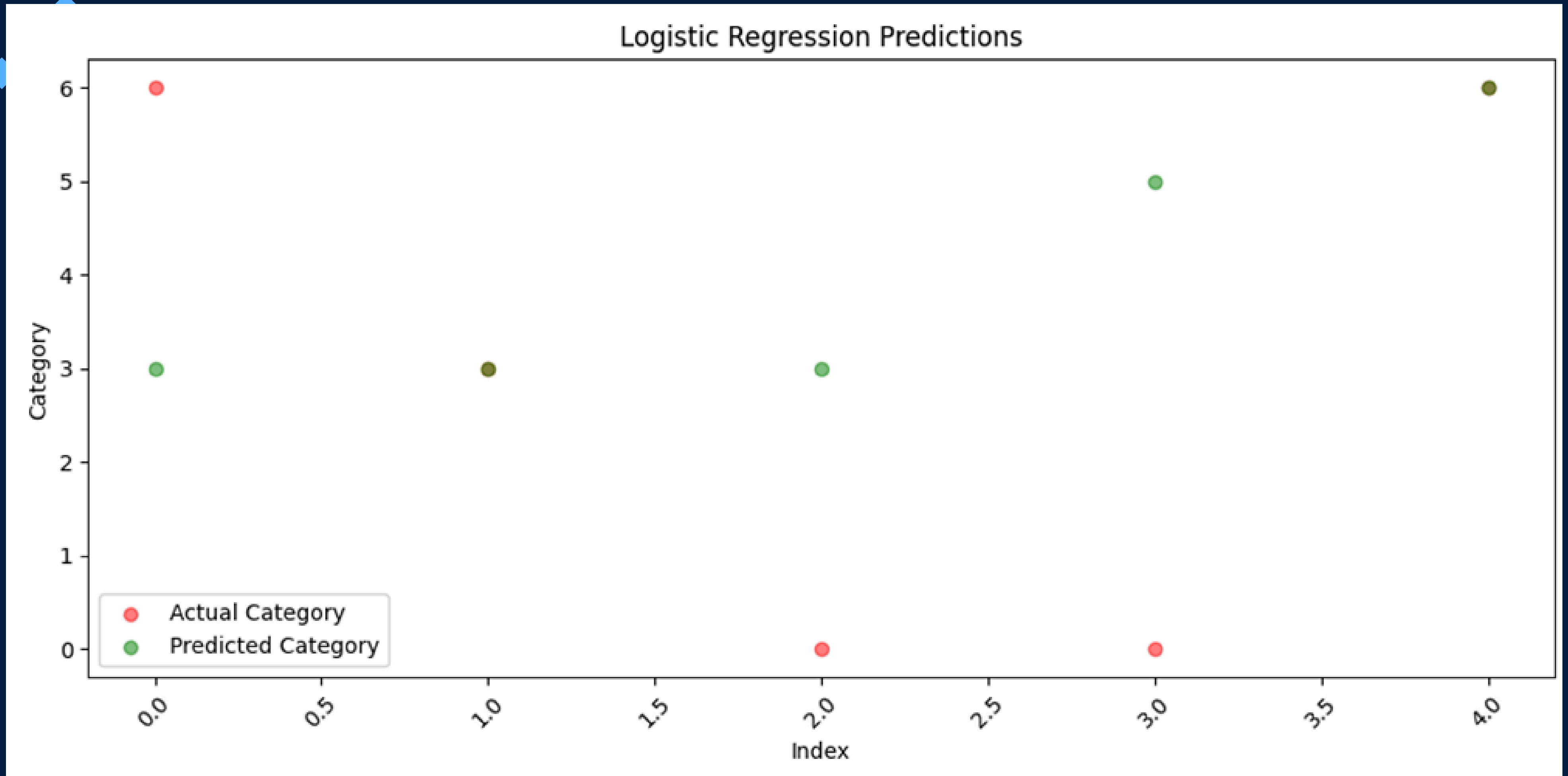
	precision	recall	f1-score	support
Hurricane Category 1	0.07	0.07	0.07	42
Hurricane Category 2	0.09	0.10	0.09	42
Hurricane Category 3	0.12	0.14	0.13	36
Hurricane Category 4	0.14	0.12	0.13	43
Hurricane Category 5	0.20	0.12	0.15	57
Tropical Depression	0.12	0.19	0.15	37
Tropical Storm	0.11	0.12	0.11	43
Accuracy			0.12	300
Macro Avg	0.12	0.12	0.12	300
Weighted Avg	0.13	0.12	0.12	300

The Random Forest model was used for classifying hurricane categories. It is an ensemble method that builds multiple decision trees and combines their predictions. To assess the model's performance, we used accuracy and visual comparisons between predicted and actual hurricane categories.



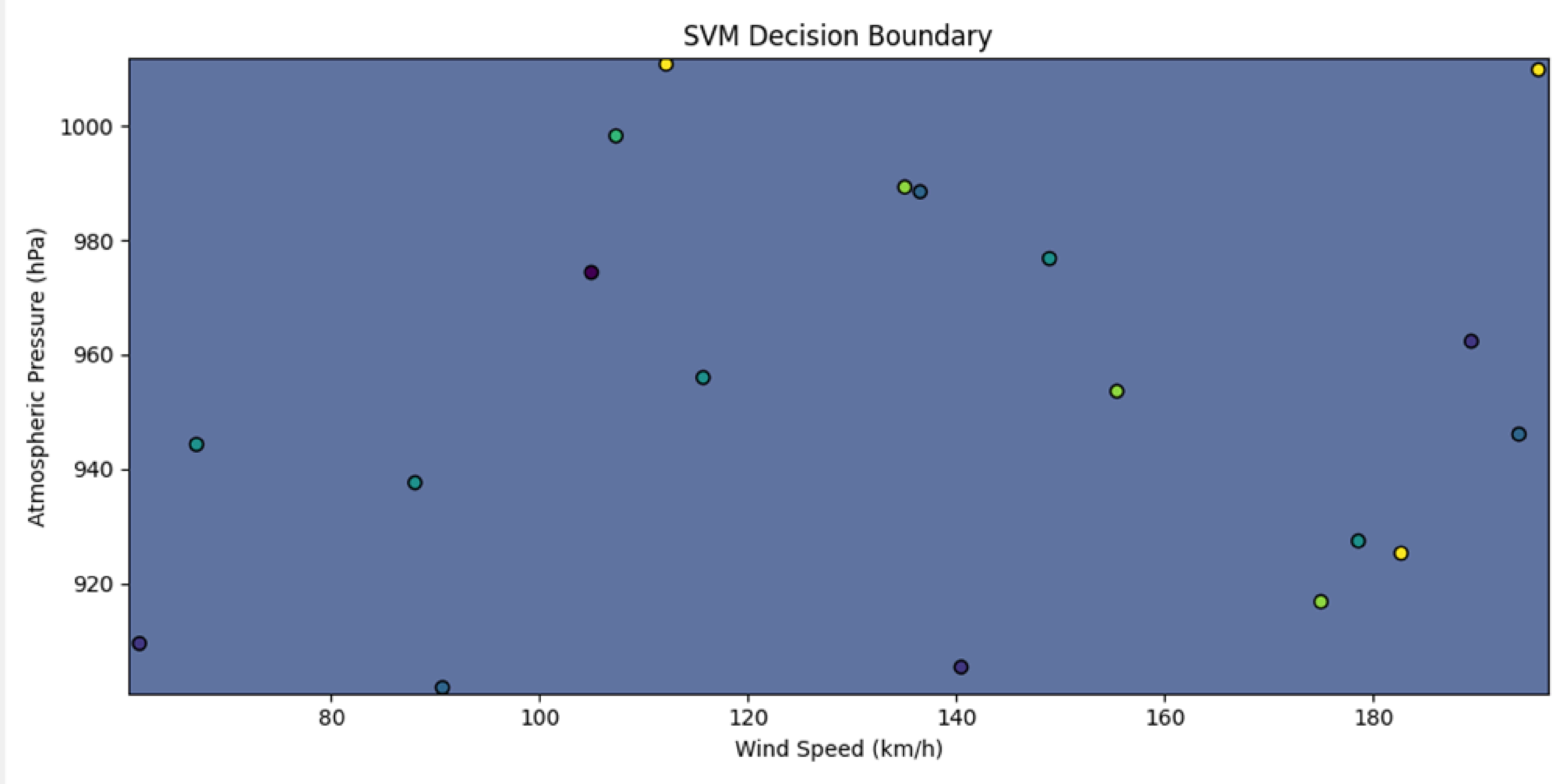


The Logistic Regression model was used to classify hurricane categories. Although logistic regression is a popular method for binary classification, it can also be used for multi-class tasks, as in this case. The histogram shows the distribution of predicted categories.



While Linear Regression is traditionally used for regression tasks, it can also be applied to classification. However, in this case, its use led to less accurate results since linear regression is not suited for categorical variable tasks. The model's predictions were rounded to match the target categories. The histogram shows how the linear regression predictions are distributed.

The Support Vector Machine (SVM) model was used for hurricane classification and proved to be the most effective of all tested models. SVM finds the optimal hyperplane for separating different classes, which is ideal for tasks with clear boundaries between categories. The plot shows the decision boundary that separates the different hurricane categories.



Client application development. Database implementation

For the database implementation, I have chosen MySQL due to its widespread use, scalability, and ease of integration with various client applications. MySQL is a powerful, open-source relational database management system (RDBMS) that is widely used for web and enterprise applications. It supports a variety of programming languages, including Python, making it an ideal choice for developing database-driven client applications.

```
CREATE DATABASE pythonlogin;
CREATE TABLE accounts (
    id INT IDENTITY(1,1) PRIMARY KEY,
    username NVARCHAR(50) NOT NULL,
    password NVARCHAR(255) NOT NULL,
    email NVARCHAR(100) NOT NULL
  );
INSERT INTO accounts (username, password, email) VALUES ('test',
'0ef15de6149819f2d10fc25b8c994b574245f193', 'test@test.com');
```

Here’s explanation of the sql-code:

1.Database Creation: The pythonlogin database is created with CREATE DATABASE statement.

2.Table Creation: The accounts table is designed to store user data. It contains four columns:

– id: A primary key, which is an auto-incremented integer.

– username: A string that stores the user's username.

– password: A hashed string that stores the user's password. This is crucial for security, as passwords should never be stored in plain text.

– email: A string that stores the user's email address.

3.Sample data: Insert an example of a user record. This user has a hashed password to ensure security.

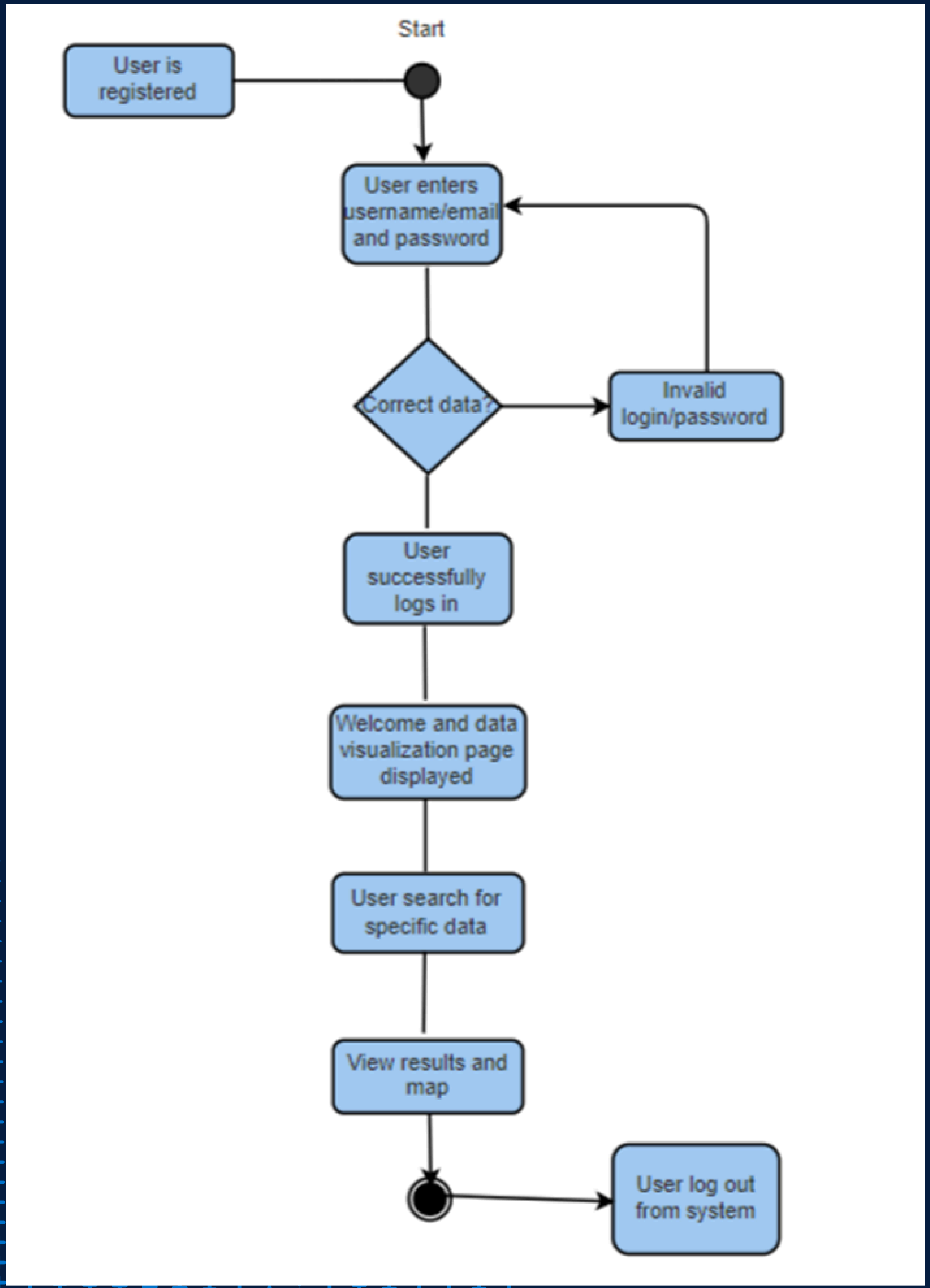
Client application development. Client application creation

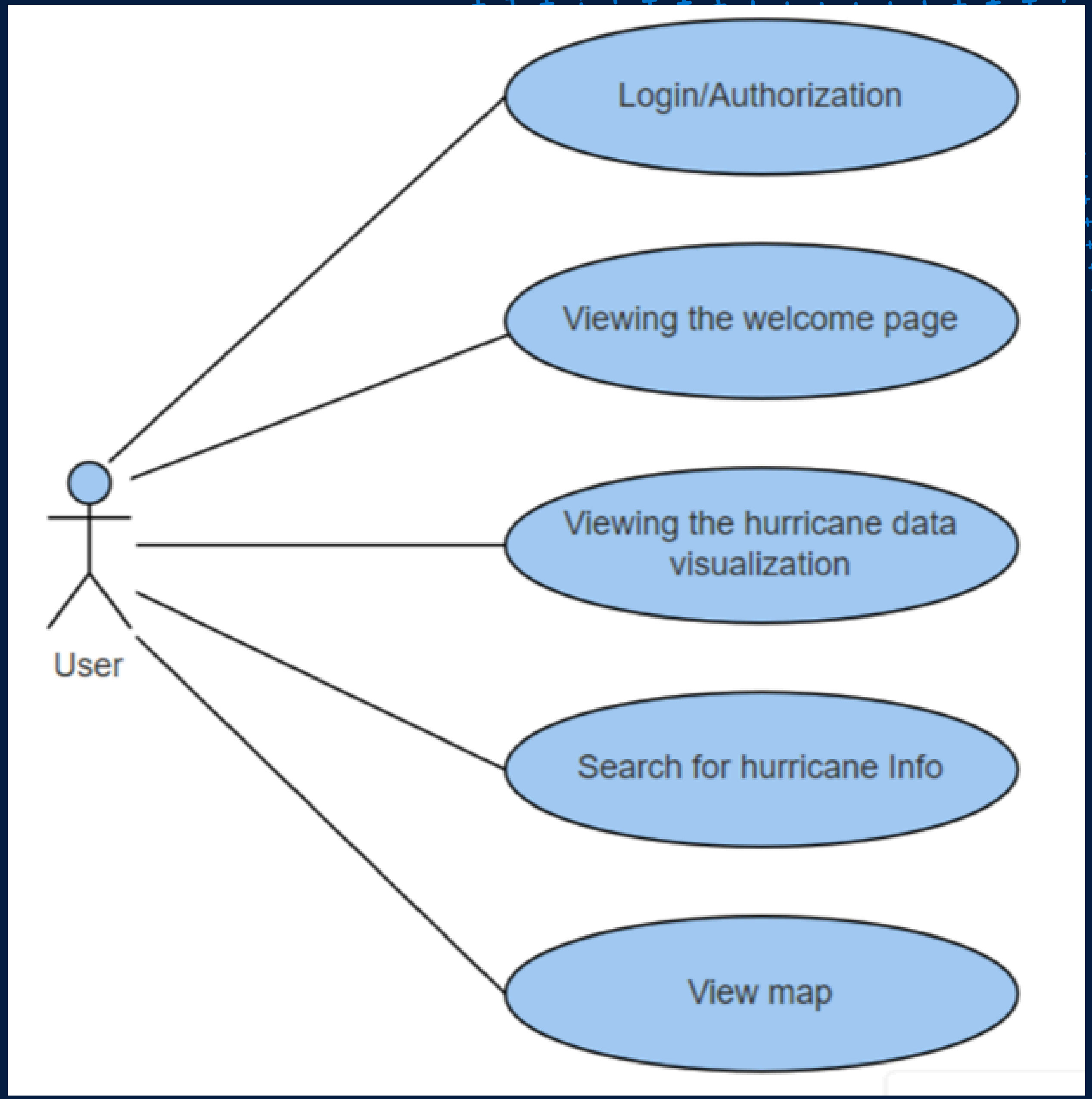
The client application for the Hurricane Dashboard was developed using PyQt5, a popular Python library for creating graphical user interfaces (GUIs). This application consists of several interconnected pages, each serving a specific function within the hurricane analysis system. The main goal of the application is to allow users to log in, register, and then interact with the hurricane data through a series of visualizations and informative features.

The following modules from PyQt5 were integral to building the application:

- QtWidgets: Contains the essential components for creating a GUI, such as buttons, labels, and text fields.
- QtGui: Provides tools for handling graphical elements such as images, fonts, and colors.
- QtCore: Used for time-based events, such as refreshing data or updating the display at regular intervals.
- QtWebEngineWidgets: Used for embedding web content, such as maps or online data, into the application.
- matplotlib: Although not a part of PyQt5, matplotlib was used in conjunction with PyQt5 for rendering various charts and graphs. These charts are embedded into the PyQt5 interface using QGraphicsView or QLabel.

This diagram for the Hurricane Dashboard Application outlines the process flow of a user's interaction with the system, comprising five key steps.





The flowchart illustrates the user journey through the Hurricane Dashboard application, which consists of several steps. After logging in or registering, users are directed to the welcome page, where they can begin their analysis. From there, they can access the data visualization page, displaying various graphs and maps. Users can explore and interact with the visualizations, switch between sections, and search for specific hurricane data. Finally, they can view detailed information about hurricanes or analyze results to gain insights, with the system displaying interactive, meaningful data

Conclusion

The Hurricane Dashboard project successfully demonstrated the application of machine learning models to predict hurricane categories based on various meteorological data points, such as wind speed and atmospheric pressure. By utilizing advanced machine learning algorithms such as Random Forest, Logistic Regression, and Support Vector Machines (SVM), the project provided valuable insights into the capabilities and limitations of these models in predicting hurricane severity.

This project contributes to the field of machine learning and intelligent systems by providing an example of how predictive models can be used in meteorology to classify hurricane categories. The findings show that while machine learning models, particularly ensemble methods like Random Forest, can offer accurate predictions, there is still room for improvement, especially in categories with overlapping features. This highlights the potential for further exploration into feature engineering and model fine-tuning.

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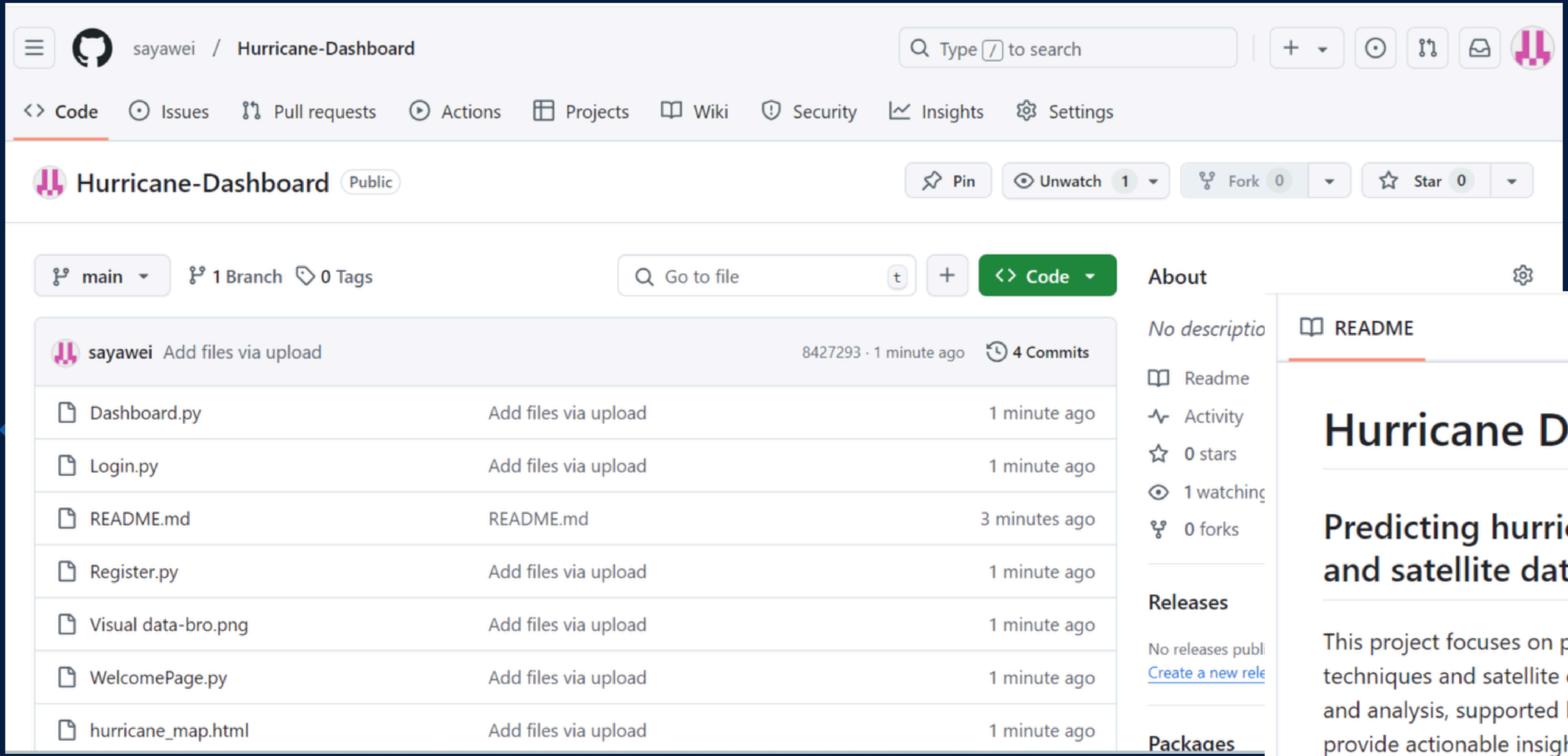

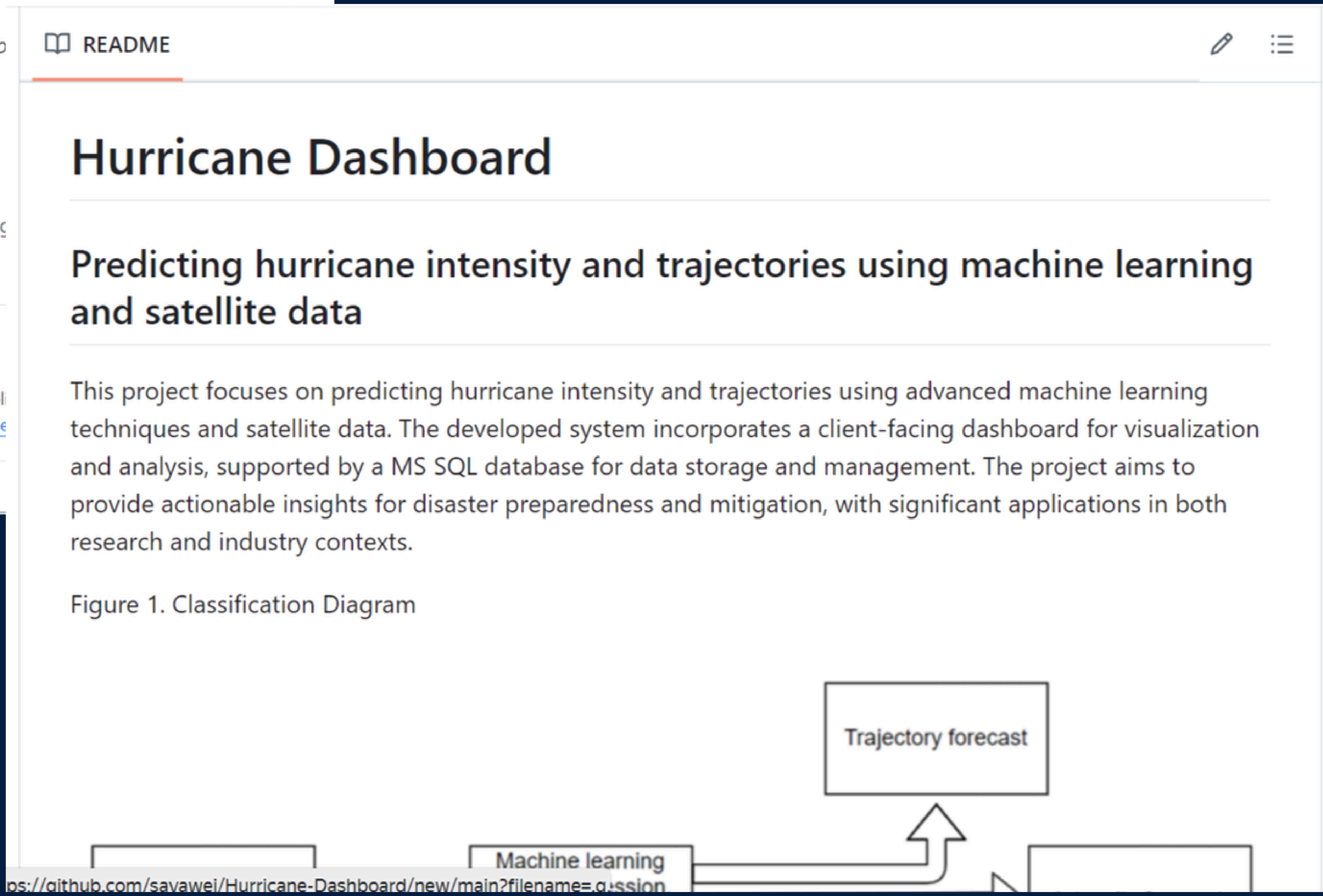

https://github.com/sayawei/Hurricane-Dashboard

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Thank's for your attention!

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