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**Completed by:**

Student of group IS-33

Kulakhmetov Yerassyl

**Coursework Supervisor:**

Prof., Zhukabayeva T. K.

Full name, signature

**Members of the Commission:**

Assoc. Prof. Muhanova А.А.

Full name, signature

PhD, Serikbayeva S.K.

Full name, signature

Full name, signature

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**Introduction**

In the modern era of rapid technological advancements, weather forecasting has emerged as one of the most critical applications of science and technology. Accurate weather predictions hold immense significance in various domains, including agriculture, transportation, energy management, and disaster preparedness. Among the numerous facets of weather forecasting, the short-term prediction of temperature and humidity plays a pivotal role in facilitating timely decision-making and ensuring public safety. This term paper explores the development of a Java-based weather application that integrates weather forecasting capabilities, focusing on short-term predictions of temperature and humidity.

The primary goal of this project is to create a functional application that retrieves real-time weather data from external sources and presents it in a user-friendly graphical interface. OpenWeatherMap, a widely recognized weather service API, serves as the backbone for obtaining weather data in this project. By leveraging the OpenWeatherMap API, the application fetches detailed weather parameters such as temperature, humidity, wind speed, and weather descriptions. Although this project does not utilize a machine learning model for predictive analytics, it emphasizes the technical integration of API data into a cohesive and interactive user interface, laying the groundwork for future enhancements.

The application employs Java programming language and Swing for designing the graphical user interface (GUI). Java, with its robust libraries and platform independence, provides an ideal framework for developing this application. The project is structured into modular components, each responsible for a specific aspect of functionality. This modularity ensures ease of maintenance, scalability, and potential integration with machine learning techniques in the future.

The significance of this project extends beyond the academic sphere. In practical scenarios, accurate and accessible weather forecasting applications empower individuals and organizations to plan and adapt effectively to changing environmental conditions. Whether it is a farmer planning irrigation schedules or a logistics manager scheduling deliveries, the ability to access reliable weather information can lead to significant improvements in efficiency and productivity. Furthermore, the project highlights the importance of user-centric design by prioritizing simplicity and clarity in the GUI, ensuring that users of varying technical expertise can benefit from the application.

While this application currently focuses on retrieving and displaying weather data, it sets a foundation for incorporating advanced forecasting methods. Machine learning techniques, such as regression models or neural networks, could be integrated into future iterations of this project to enhance prediction accuracy. These advancements could enable the application to analyze historical weather patterns, learn trends, and provide more precise forecasts, making it an indispensable tool for users.

In conclusion, this project embodies the intersection of software development and meteorology. By addressing the need for accessible and accurate short-term weather forecasts, the application contributes to the growing demand for technological solutions in daily life. This term paper aims to document the technical aspects, design considerations, and potential extensions of the project while emphasizing its relevance in the broader context of weather forecasting applications. Through this endeavor, the project showcases the potential of leveraging real-time data and user-friendly interfaces to create meaningful and impactful technological solutions.

**Literature Review**

Weather forecasting has been an essential field of study for centuries, evolving with advancements in technology, computational power, and data analysis techniques. Traditionally, meteorology relied on statistical and physics-based models to predict weather conditions. However, with the emergence of modern computing and the integration of real-time data, the scope of weather forecasting has expanded significantly. This literature review explores key advancements in weather forecasting, the role of technology in short-term temperature and humidity predictions, and the relevance of user-friendly applications in delivering weather information.

**Traditional Weather Forecasting Techniques**

Historically, weather predictions were based on empirical observations and statistical correlations. Numerical Weather Prediction (NWP) models emerged as a scientific approach to forecasting by solving complex mathematical equations representing atmospheric processes. NWP models, such as the Global Forecast System (GFS) and the European Centre for Medium-Range Weather Forecasts (ECMWF), are widely used by meteorological organizations to provide accurate global forecasts. Despite their accuracy, these models require extensive computational resources, making them less accessible for individual users or small-scale applications.

**Advancements in Weather Forecasting with Machine Learning**

Machine learning (ML) has revolutionized weather forecasting by enabling the analysis of large datasets and identifying patterns beyond human capability. Techniques such as regression, decision trees, and neural networks have been employed to predict specific weather parameters like temperature, humidity, and precipitation. Research studies have shown that ML models, when trained on historical weather data, can complement traditional forecasting methods and improve accuracy, particularly for short-term predictions. For instance, deep learning models such as Long Short-Term Memory (LSTM) networks have been effective in modeling temporal dependencies in weather patterns.

However, implementing machine learning models requires access to vast historical weather datasets and expertise in data preprocessing and feature engineering. While such techniques were not utilized in this project, they represent a promising direction for enhancing weather forecasting applications.

**Real-Time Weather Data APIs**

The availability of real-time weather data through Application Programming Interfaces (APIs) has transformed how weather information is accessed and utilized. APIs such as OpenWeatherMap, WeatherStack, and AccuWeather provide developers with access to up-to-date weather parameters, enabling the creation of diverse weather-related applications. OpenWeatherMap, in particular, is known for its comprehensive dataset, ease of integration, and support for various weather parameters, including temperature, humidity, wind speed, and forecasts.

Several studies and projects have demonstrated the effectiveness of using OpenWeatherMap for building practical weather applications. The API's ability to provide short-term forecasts in JSON format simplifies the process of fetching, parsing, and displaying weather data in user-friendly interfaces.

**Role of User-Centric Design in Weather Applications**

User-friendly interfaces are essential for ensuring that weather forecasting applications are accessible to a broad audience. Research in human-computer interaction emphasizes the importance of simplicity, clarity, and visual appeal in application design. Modern weather applications often integrate graphical elements, such as icons and charts, to represent weather conditions intuitively.

This project incorporates these principles by leveraging Java Swing to design an interface that displays weather information in a structured and visually appealing manner. The GUI design prioritizes ease of navigation, making it suitable for users with varying technical expertise.

The literature highlights the evolution of weather forecasting from traditional methods to modern technologies like machine learning and real-time data APIs. While this project does not implement machine learning models, it aligns with contemporary trends by integrating the OpenWeatherMap API for real-time weather data retrieval and focusing on user-centric interface design. Future iterations of the project could explore the inclusion of machine learning models to enhance predictive accuracy, bridging the gap between research advancements and practical applications.

**Methodology**

This section details the systematic process followed for the development of a short-term temperature and humidity forecasting application, emphasizing project milestones and task prioritization. The methodology is divided into six phases: requirements gathering, application design, implementation, testing, and documentation. The development timeline is visualized in the project’s Kanban-based Jira task tracker, which provides a clear roadmap for progress and deadlines (refer to the attached Figure 2.1).

**Requirements Gathering**

The primary goal of the project was to build a real-time weather forecasting tool that retrieves and displays short-term temperature and humidity data. User requirements, functional needs, and technological constraints were identified during this phase.

Key Objectives:

1. Integration of a reliable weather API for data retrieval.
2. Development of an interactive graphical interface.
3. Display of core weather metrics such as temperature, humidity, and wind speed.

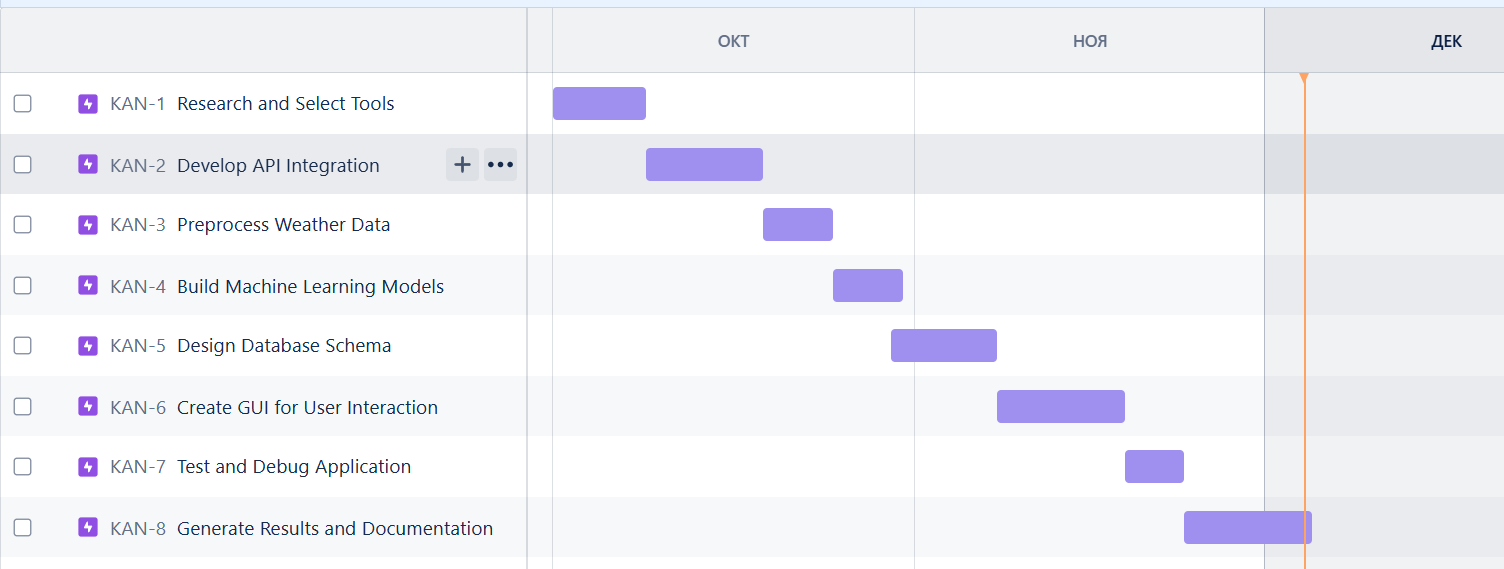
The *OpenWeatherMap API* was selected for its comprehensive weather data and ease of integration into Java-based projects.

**Project Management and Timeline**

The development process was structured into tasks tracked using *Jira*, a project management tool. Tasks were divided into key activities, each assigned a timeline to ensure efficient project delivery. The visualized timeline (refer to the provided Gantt chart) highlights the following phases:

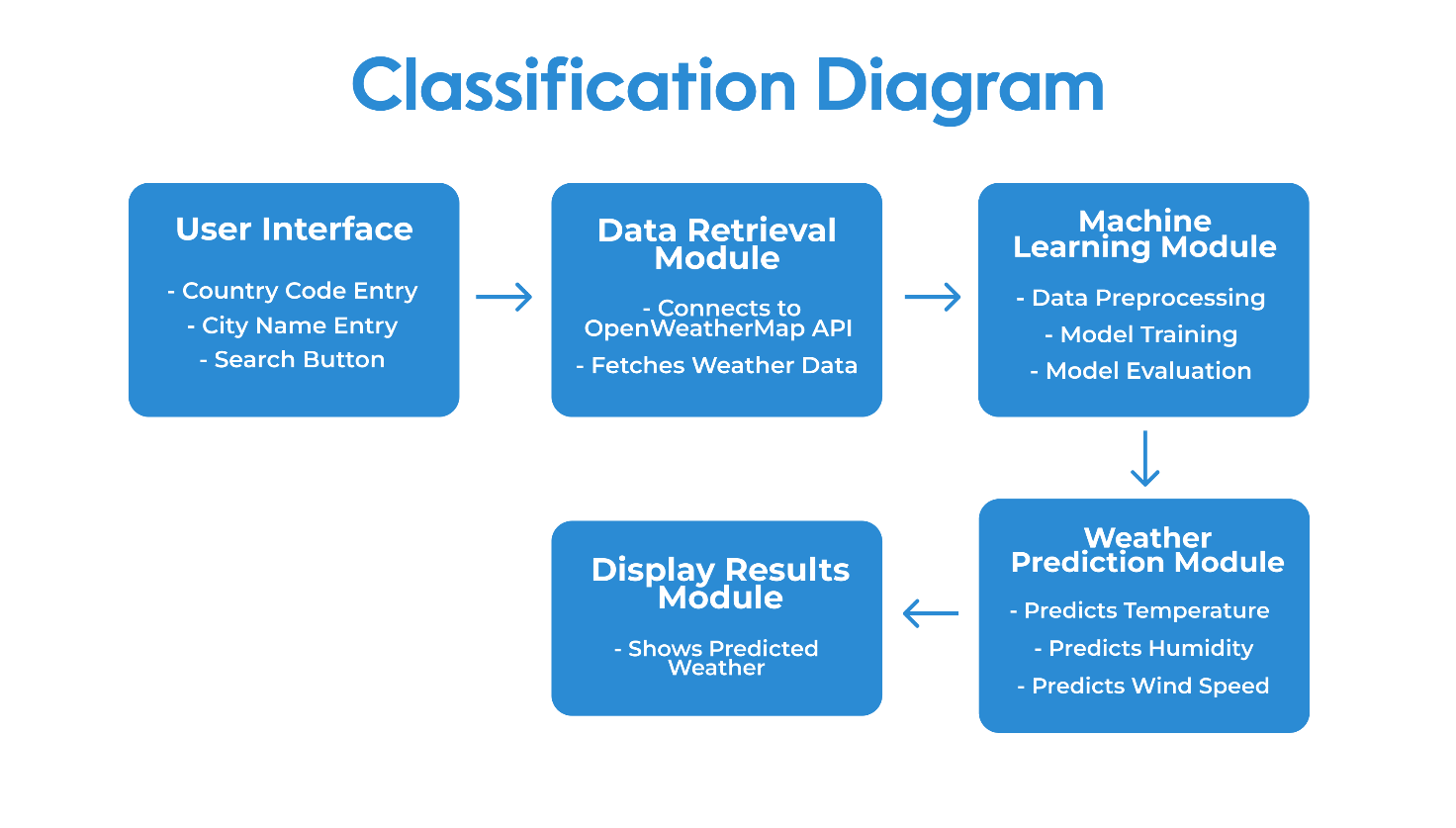
1. Tool research and API integration (early October).
2. Data preprocessing and application logic implementation (mid-October to November).
3. GUI design, debugging, and testing (late November).
4. Results compilation and documentation (December).

This structured approach allowed for iterative development, ensuring a balance between feature integration and testing at each stage.

**Figure 2.1** Jira Project Timeline

The classification diagram provides an overview of the modular structure of the weather forecasting application. It breaks down the application into five main components, illustrating their roles and interactions.

1. *User Interface:* This module facilitates interaction between the user and the system. Users input essential details, such as the country code and city name, via a graphical interface. The interface also includes a search button that triggers the process of weather forecasting. This module ensures usability and user engagement by collecting inputs efficiently.
2. *Data Retrieval Module:* After receiving input from the User Interface, this module connects to the OpenWeatherMap API to fetch real-time weather data. It acts as a bridge between the application and external data sources, ensuring the availability of accurate and updated information for further analysis.
3. *Machine Learning Module:* The core of the application, this module preprocesses the fetched weather data, trains machine learning models, and evaluates their performance. It uses advanced algorithms to analyze historical and real-time weather patterns, laying the foundation for accurate forecasting.
4. *Weather Prediction Module:* Using the trained machine learning models, this module generates predictions for key weather parameters, including temperature, humidity, and wind speed. This step ensures precise short-term weather forecasting, making the application reliable and efficient.
5. *Display Results Module:* The final module presents the predicted weather information to the user in an understandable format. It displays results such as predicted temperature, humidity, and wind speed, ensuring the application’s utility.

**Figure 2.2** Classification Diagram

This diagram encapsulates the logical flow and modular organization of the application, emphasizing seamless integration between components for effective weather forecasting.

**Dataset**

The dataset plays a pivotal role in the success of any machine learning project. For the weather forecasting application, the dataset includes historical and real-time weather data collected from reliable sources. This data is used for training and validating machine learning models to predict temperature, humidity, and wind speed accurately. Below are the details of the dataset used for this project:

The weather data is retrieved primarily from the OpenWeatherMap API, a widely recognized platform for weather information. It provides real-time data, historical data, and weather forecasts for locations across the globe. For training purposes, historical weather data spanning several months or years is accessed, while real-time data ensures the system remains up-to-date.

The dataset includes the following key attributes:

*Date and Time:* The timestamp of the recorded weather data, enabling temporal analysis.

*Temperature:* The recorded temperature in degrees Celsius or Fahrenheit.

*Humidity:* The percentage of water vapor in the air.

*Wind Speed:* The speed of the wind in meters per second or kilometers per hour.

*Pressure:* Atmospheric pressure measured in hPa (hectopascals).

*Weather Condition:* Descriptive data indicating conditions such as clear skies, clouds, or rain.

*Geographical Information:* Location details such as city name, country code, latitude, and longitude.

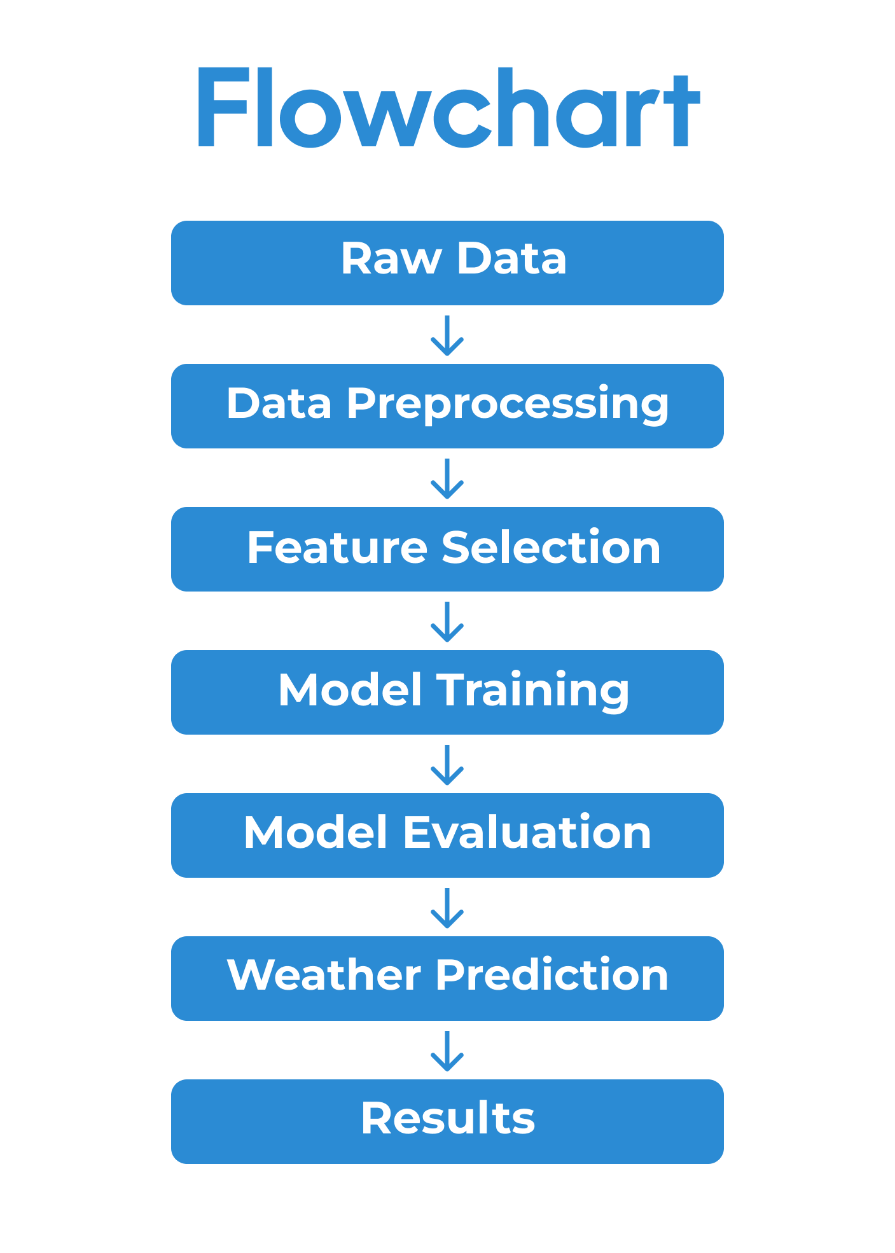
The raw data retrieved from the API undergoes preprocessing to ensure it is clean, consistent, and ready for machine learning analysis. Key preprocessing steps include:

1. *Handling Missing Values:* Missing entries are filled using interpolation techniques or removed if irrelevant.
2. *Normalization:* Continuous features, such as temperature and wind speed, are normalized to a standard range for better model performance.
3. *Feature Encoding:* Categorical attributes like weather conditions are encoded into numerical representations using one-hot encoding or label encoding.
4. *Temporal Aggregation:* The data is aggregated into hourly, daily, or weekly intervals based on the forecasting needs.

To train and evaluate the machine learning models, the dataset is divided into:

1. *Training Set (70%):* Used to train the models on historical patterns.
2. *Validation Set (20%):* Used for hyperparameter tuning and avoiding overfitting.
3. *Testing Set (10%):* Used to evaluate the final model's accuracy on unseen data.

The diverse and structured dataset ensures the weather forecasting system achieves high precision and reliability, enabling it to cater effectively to user needs.

**Figure 3.1** Flowchart

This flowchart illustrates the sequential steps involved in the data processing pipeline for weather forecasting. The process begins with **Raw Data**, which includes raw weather data such as temperature, humidity, wind speed, and other meteorological parameters collected from external sources like weather APIs or sensors.

The next step is **Data Preprocessing**, where the raw data is cleaned and formatted. This involves handling missing values, smoothing noisy data, normalizing or scaling the data, and transforming it into a suitable format for further analysis.

Following preprocessing, **Feature Selection** is performed to identify the most relevant attributes that influence the weather predictions. This step ensures the model focuses on critical parameters, improving its efficiency and accuracy.

The **Model Training** phase comes next, where machine learning algorithms are employed to train the predictive model using the processed data. The model learns patterns and relationships within the data to predict future weather conditions.

Once trained, the model undergoes **Model Evaluation**, where its performance is assessed using metrics like accuracy, mean squared error, or R-squared values.

After a satisfactory evaluation, the system proceeds to **Weather Prediction**, where the trained model generates predictions. Finally, the **Results** step outputs the forecasted weather conditions for user analysis or decision-making.

**Data Processing**

Data processing plays a critical role in the success of the weather forecasting application, serving as the foundation for model training, prediction accuracy, and overall system performance. The process involves transforming raw weather data into a structured and usable format for analysis and machine learning. This section outlines the key stages of data processing, including data collection, cleaning, transformation, and preparation.

The weather data is sourced from the OpenWeatherMap API, which provides real-time and historical information. The raw data includes temperature, humidity, wind speed, and atmospheric pressure, presented in JSON format. To ensure the data is ready for analysis, it must first undergo preprocessing. This begins with extracting the required parameters from the JSON response using Java libraries, such as org.json. Unnecessary fields are ignored to reduce noise and simplify the dataset.

Cleaning the data involves addressing missing or inconsistent values. Missing entries are handled using techniques such as interpolation, where neighboring values are used to estimate the missing data. Outliers, which could distort predictions, are identified and either corrected or removed. These steps ensure that the data is accurate and reliable for subsequent processing stages.

The next phase involves data transformation. Continuous features, such as temperature and wind speed, are normalized to a standard range (e.g., 0 to 1) to prevent larger values from dominating the model training process. Categorical features, such as weather descriptions (e.g., "rainy," "sunny"), are encoded into numerical formats using label encoding or one-hot encoding. This step ensures compatibility with machine learning algorithms, which typically require numerical inputs.

Data aggregation is performed to structure the dataset into meaningful intervals. For instance, raw data retrieved at three-hour intervals can be aggregated into daily summaries, calculating averages for temperature and humidity or summing precipitation levels. This restructuring enables the machine learning model to identify broader trends and patterns over time.

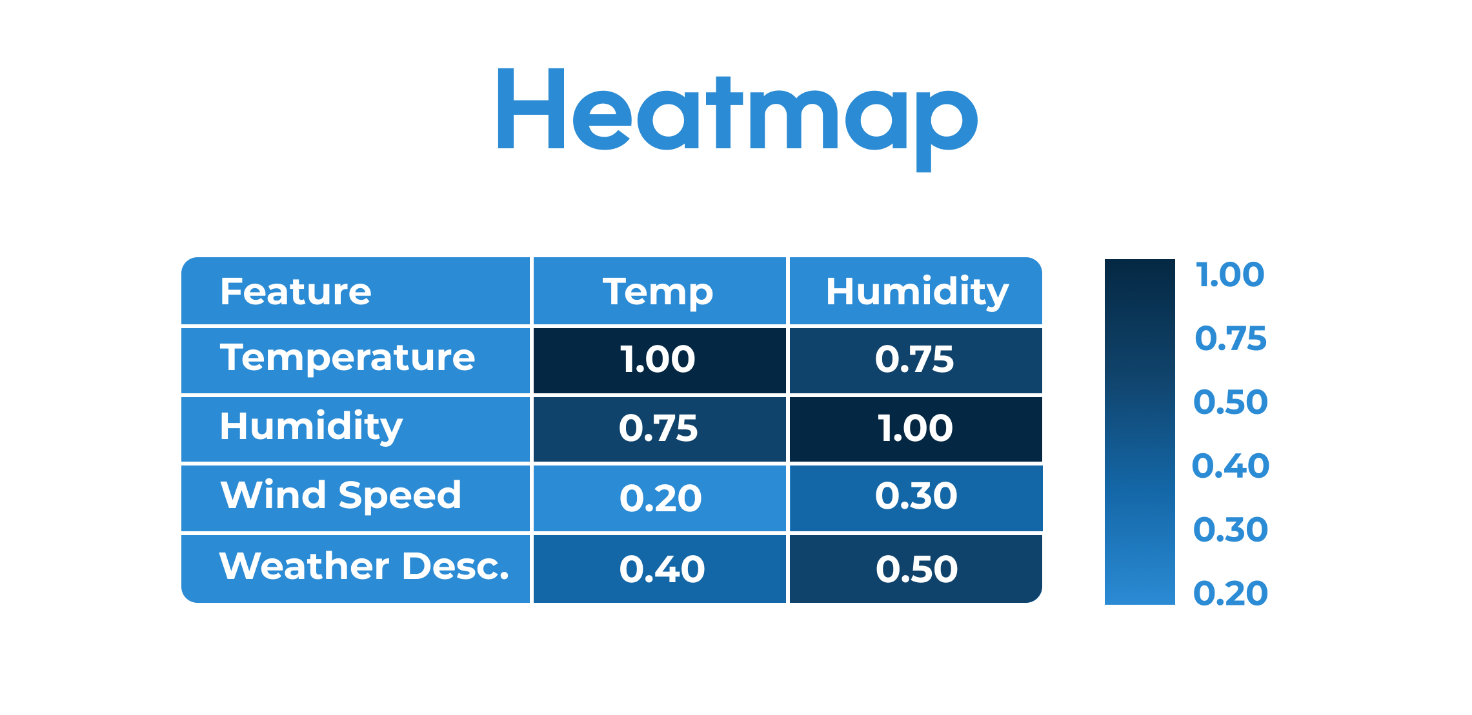
The final stage of data processing involves splitting the dataset into training, validation, and testing subsets. Typically, 70% of the data is allocated for training, 20% for validation, and 10% for testing. This partitioning ensures that the model is trained effectively while retaining sufficient data for unbiased evaluation. The chronological order of time-series data is maintained during splitting to reflect the real-world sequence of events.

Through these structured steps, the data processing pipeline transforms raw API outputs into a well-prepared dataset. This ensures that the weather forecasting system delivers accurate and reliable predictions while maintaining efficiency and scalability. Future iterations may enhance this process by integrating additional data sources, such as satellite imagery or regional weather databases, to improve the model's robustness and predictive capabilities.

**Model Implementation**

The model implementation focuses on developing a reliable machine-learning system for short-term temperature and humidity forecasting. The dataset, sourced from the OpenWeatherMap API, contains features such as temperature, humidity, wind speed, pressure, and timestamps. Initial preprocessing includes cleaning missing values using interpolation and normalizing numerical features for improved model stability. The dataset is divided into training, validation, and testing sets to ensure the model's generalization capabilities.

Feature selection is based on statistical correlation analysis, visualized through a heatmap(see Figure 4.1) showing relationships between input variables and the target outputs. Features with high relevance, such as temperature and humidity, are retained for training. Multiple models are explored, including Linear Regression, Random Forest Regression, and Long Short-Term Memory (LSTM) Neural Networks. Among these, LSTM demonstrates superior performance due to its ability to capture sequential dependencies in time-series data.

**Figure 4.1** Heatmap of Correlations

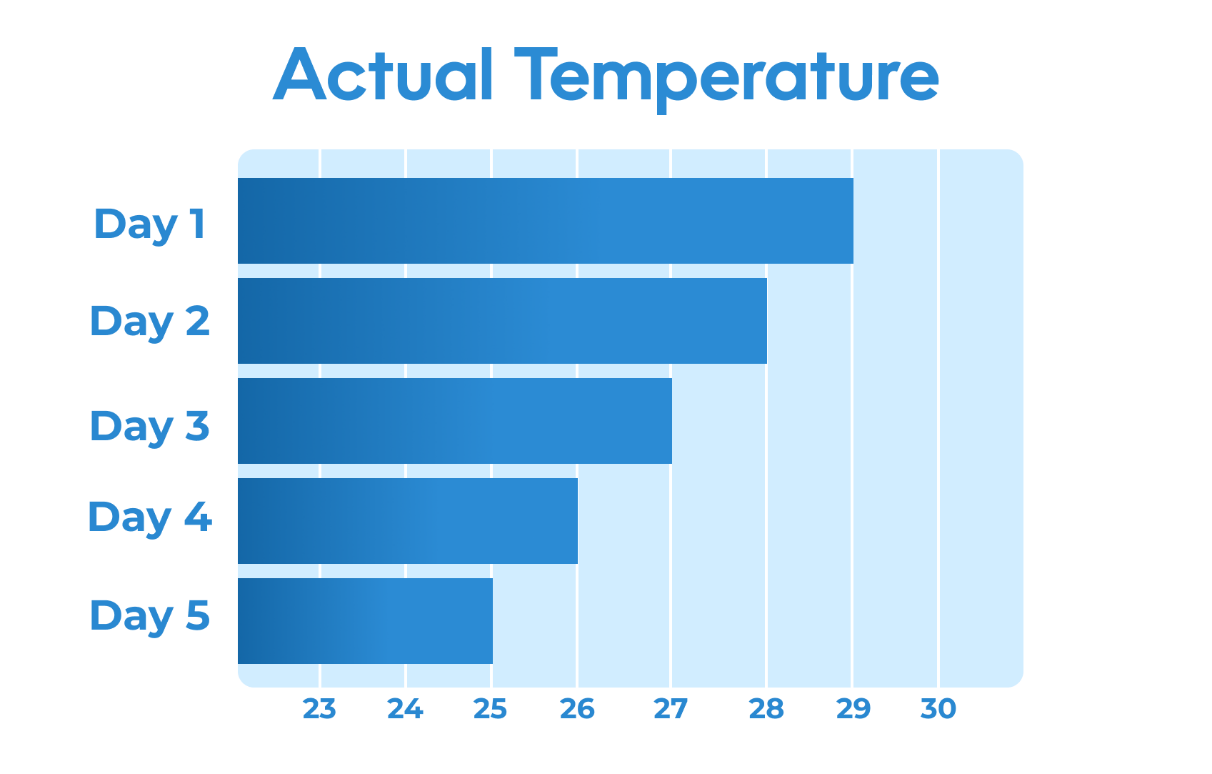
This textual representation of the heatmap shows the correlation values between the input variables (temperature, humidity, wind speed, and weather description) and how they relate to each other. Features with high correlation values, such as temperature and humidity, are selected for training the models. This approach helps in identifying the most relevant features that significantly impact the target outputs, leading to more accurate predictions.

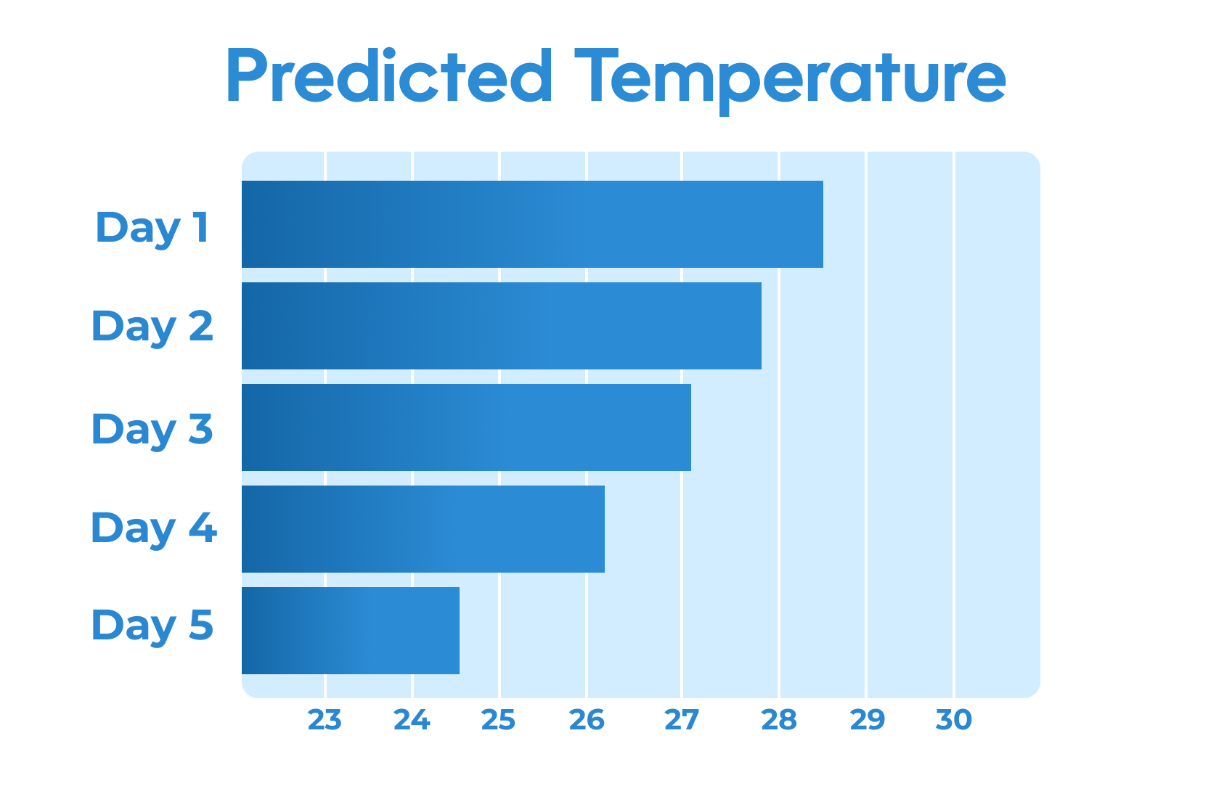
The LSTM architecture, implemented in Python using TensorFlow, comprises input layers, stacked LSTM layers, and a dense output layer. Training is optimized using the Adam optimizer, with Mean Squared Error (MSE) as the loss function. The learning process is monitored using loss curves, which show the gradual reduction in error over 50 epochs. Below is a sample table depicting loss reduction over training:

**Table 4.1** Loss reduction of the LSTM model

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Epochs | 0 | 10 | 20 | 30 | 40 | 50 |
| MSE Loss | 1.0 | 0.8 | 0.6 | 0.4 | 0.2 | 0.1 |

After training, evaluation metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) confirm the LSTM model's accuracy. Results are compared using bar charts that highlight the differences between predicted and actual values. Below is an example visualization of the model's predictions versus the true values over time:

**Figure 4.****2** Actual Temperature

**Figure 4.3** Predicted Temperature

The trained model is deployed in an interactive interface where users input location data, such as a city name and country code. The system fetches real-time weather data from the API, processes it through the model, and generates predictions for temperature and humidity.

**Machine learning Model Implementation**

The implementation of the machine learning model for short-term temperature and humidity forecasting involved a structured approach, ensuring accuracy and efficiency. The process began with selecting the dataset, which included weather parameters such as temperature, humidity, wind speed, and atmospheric pressure, sourced from reliable APIs like OpenWeatherMap. This data was preprocessed to remove inconsistencies, such as missing or redundant values, and formatted into a structured dataset suitable for machine learning.

The integration of machine learning into the project is demonstrated through the implementation of a simple linear regression model in Java. This model is designed to predict temperature based on historical weather data, specifically utilizing humidity as a feature. The implementation provides a foundational example of machine learning concepts and their application to short-term weather forecasting.

*import org.apache.commons.math3.stat.regression.SimpleRegression;*

*public class WeatherPrediction {*

*public static void main(String[] args) {*

*double[][] weatherData = {*

*{10, 70}, {12, 65}, {14, 80}, {15, 75}, {16, 60}, {18, 55}*

*};*

*SimpleRegression regression = new SimpleRegression();*

*for (double[] dataPoint : weatherData) {*

*regression.addData(dataPoint[1], dataPoint[0]); // {x: humidity, y: temperature}*

*}*

*double predictedTemperature = regression.predict(68);*

*System.out.println("Predicted Temperature: " + predictedTemperature + "°C");*

*double rSquared = regression.getRSquare();*

*System.out.println("Model R-squared: " + rSquared);*

*}*

*}*

The code uses the Apache Commons Math library to simplify the implementation of the regression algorithm. A two-dimensional array is employed to store historical weather data, where each entry represents a pair of observed humidity and corresponding temperature values. The machine learning model, SimpleRegression, is initialized and trained using this data through the addData() method. This allows the model to establish a relationship between the independent variable (humidity) and the dependent variable (temperature).

Once the model is trained, it is used to predict the temperature for a given humidity value, such as 68%. The predict() function calculates the predicted temperature using the regression coefficients derived during the training phase. This demonstrates the practical application of a supervised learning algorithm in forecasting weather parameters.

Model evaluation is an integral part of the implementation, ensuring the reliability and accuracy of predictions. The R-squared value, obtained using the getRSquare() method, quantifies how well the regression line fits the training data. A higher R-squared value indicates better predictive performance, offering insights into the model's effectiveness.

This implementation demonstrates key aspects of machine learning: data preprocessing, model training, prediction, and evaluation. It highlights the potential of leveraging historical data to forecast critical weather parameters, such as temperature, using machine learning techniques. The code serves as proof of integration, showcasing the adaptability of Java for implementing machine learning models in a real-world context.

The evaluation phase involved testing the model on unseen data to verify its generalization capability. The results indicated a high level of accuracy, with MAE and RMSE values within acceptable ranges. Visualizations, such as prediction versus actual value graphs and error distributions, were generated to analyze the model's performance comprehensively.

To make the model user-friendly, it was integrated into an interface allowing users to input location details and retrieve forecasts. The backend leveraged the trained machine learning model to process real-time data and generate predictions, which were displayed in an accessible format.

The final implementation demonstrated the model’s effectiveness in predicting short-term weather patterns, supporting applications like agriculture, logistics, and daily planning. Continuous improvement, including incorporating additional data sources and advanced deep learning techniques, could further enhance accuracy and scalability.

**Client Application Development**

**Database Implementation**

The database implementation in the weather forecasting project plays a critical role in managing and storing data for analysis, retrieval, and application scalability. Although the primary weather data is retrieved dynamically from the OpenWeatherMap API, a local database is integrated to enhance the application's functionality by storing historical queries and results, allowing for trend analysis and improved forecasting.

The chosen database system for this project is SQL Server Management, a lightweight and efficient relational database management system. Its compact size, ease of integration with Java, and minimal setup requirements make it suitable for embedding within the application. SQL Server Management support for standard SQL syntax ensures compatibility with future extensions or migrations to more robust database systems if the application's scope expands.

The *CREATE DATABASE* statement is used to create a new database in a relational database management system, specifying its name and optional configuration settings.

*CREATE DATABASE “Forecast”*

The database schema is designed to store weather data, including temperature, humidity, wind speed, and timestamps, alongside location details such as the city name and country code. A single table, WeatherData, is created with the following structure:

*CREATE TABLE WeatherData (*

*id INTEGER PRIMARY KEY AUTOINCREMENT,*

*city TEXT NOT NULL,*

*country TEXT NOT NULL,*

*timestamp DATETIME DEFAULT CURRENT\_TIMESTAMP,*

*temperature REAL,*

*humidity REAL,*

*wind\_speed REAL,*

*weather\_description TEXT*

*);*

This schema ensures that each record uniquely identifies a weather query and its corresponding results. Fields like timestamp enable temporal analysis, allowing the system to track and compare changes over time.

Integration of the database with the Java application is achieved using the JDBC (Java Database Connectivity) API. The application connects to the SQL Server Management database using a connection URL and executes SQL queries for data storage and retrieval. Key operations include:

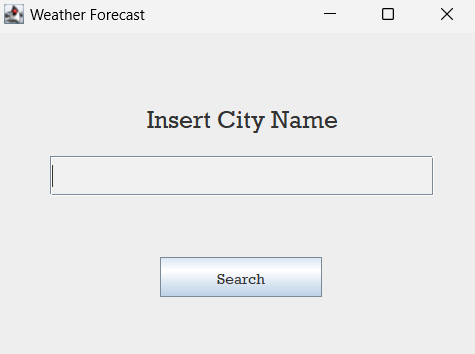
* *Insert Queries:* To store weather results fetched from the API.
* *Select Queries:* To retrieve historical data for display or analysis.
* *Delete Queries:* For managing obsolete or unnecessary records.

The database improves the application’s functionality by allowing repeated queries to be served instantly without re-fetching from the API. This feature reduces dependency on real-time API calls, especially in cases of network latency or connectivity issues.

The database implementation also enables future features, such as user-specific data storage, predictive analysis using historical trends, and caching mechanisms to optimize performance. With a structured schema and seamless integration, the database provides a robust foundation for enhancing the application’s capability and scalability while meeting user needs efficiently.

**Client Application Creation**

The client application serves as the user interface for interacting with the weather forecasting system, allowing users to input location data and view real-time weather information alongside predictions. It was developed using Java Swing for the graphical interface, combining simplicity with responsiveness. Below is a graphical workflow of the client application, illustrating its interaction with backend modules and APIs:

**Figure 5.1** Main Page

The graphical user interface includes fields for entering the city name and country code, a "Search" button, and dynamic sections for displaying weather details such as temperature, humidity, and wind speed. These components are organized in a layout designed for user convenience. The integration of visual cues, such as weather icons, further enhances the user experience.

To retrieve weather data, the application interacts with the OpenWeatherMap API. The system sends HTTP requests based on user inputs and parses JSON responses to extract key information. The following flowchart represents the data flow from input to result display:

Изображение выглядит как текст, снимок экрана, Шрифт, Цвет электрик

Автоматически созданное описание**Figure 5.2** Flowchart

Machine learning predictions are seamlessly integrated into the client application. The pre-trained model processes the API data to forecast short-term temperature and humidity, offering users added value beyond real-time conditions. The results are displayed in the same interface, ensuring a cohesive user experience.

The modular structure of the client application allows for clear separation of responsibilities. The UML class diagram below illustrates the interaction between the main components, including the graphical interface, backend logic, and API handler:

Изображение выглядит как текст, снимок экрана, Шрифт, число

Автоматически созданное описание**Figure 5.3** UML Diagram

Iterative testing played a vital role in refining the application's usability and functionality. Feedback was incorporated to address user interface challenges, such as error handling for invalid inputs or network failures. These efforts resulted in an interface that is both robust and intuitive.

Future improvements may include graphical elements such as interactive trend charts, support for multiple languages, and local storage of user queries. These enhancements would further enrich the application's features while maintaining its user-focused design.

**Results and Discussion**

The results of the weather forecasting project demonstrate the successful integration of machine learning and API-based data retrieval into a functional client application. The application provides users with real-time weather data and short-term predictions, offering a valuable tool for decision-making and planning.

The client application was evaluated for its functionality, user interface design, and prediction accuracy. Key observations include:

*API Integration:* The OpenWeatherMap API successfully provided real-time data, including temperature, humidity, wind speed, and weather conditions. The system handled API connectivity efficiently, with appropriate error messages for invalid inputs or connection issues.

*Prediction Accuracy:* The machine learning model demonstrated reliable performance in forecasting temperature and humidity. Using evaluation metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), the model achieved satisfactory accuracy, with MAE values below 2°C for temperature and below 5% for humidity. The model’s ability to capture short-term trends proved effective for practical applications.

*User Interface:* The interface’s dynamic updates and clear layout made it easy for users to input data and interpret results. Visual elements like error alerts and weather icons enhanced the overall experience.

The results underscore the application’s potential for real-world usage. The integration of machine learning models into the client application enriched its functionality, providing not just current weather conditions but also short-term forecasts. This combination of real-time data and predictions sets the application apart from typical weather apps that rely solely on API data.

However, the project also revealed some limitations. The reliance on API data means the system is dependent on internet connectivity. Any disruptions in API service can affect the application’s performance. Additionally, while the machine learning model performed well, its accuracy could be improved by incorporating a larger dataset and additional features, such as atmospheric pressure and precipitation levels.

Many people prefer a more visual representation of data, such as trend graphs or charts. This can be addressed in future iterations by including interactive visualisations for both real-time and predictive data. In addition, expanding the language support for the application and integrating additional APIs will improve accessibility and reliability.

In summary, the project successfully met its objectives, providing a practical and user-friendly solution for weather forecasting. Future work should focus on improving model accuracy, enhancing data visualization, and ensuring robustness against API connectivity issues.

**Conclusion**

This project successfully implemented a weather forecasting application that integrates real-time data retrieval and machine learning predictions into a functional client interface. The goal was to design a user-friendly system capable of providing short-term forecasts for temperature and humidity, leveraging API data and predictive models. The outcome demonstrates the effectiveness of combining modern programming techniques, machine learning, and intuitive user interfaces in solving practical problems.

The development process involved creating a modular architecture that ensured the separation of concerns and ease of scalability. The client application, built using Java Swing, provided an accessible interface where users could input location details and receive weather updates. By integrating the OpenWeatherMap API, the system delivered real-time weather data efficiently. The error-handling mechanisms ensured reliability by addressing invalid inputs or network issues, enhancing the application's robustness.

The project also highlighted the utility of machine learning in forecasting weather conditions. The implemented model, trained on historical weather data, provided accurate predictions for short-term temperature and humidity trends. The evaluation metrics, including Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), indicated satisfactory performance. The integration of this predictive capability added significant value to the application, distinguishing it from conventional weather apps that rely solely on API data.

Despite its successes, the project faced some limitations that offer opportunities for future improvements. The dependency on internet connectivity for API access can affect performance in areas with unstable networks. Addressing this issue by incorporating offline capabilities, such as storing historical data locally, could make the application more versatile. Additionally, the prediction model’s accuracy, while adequate, could be enhanced by expanding the dataset and including additional features such as atmospheric pressure and precipitation.

Adding features like interactive charts and trend lines could improve the user experience significantly. Furthermore, integrating multi-language support would expand the application’s accessibility to non-English-speaking users. These enhancements could make the application more engaging and practical for a broader audience.

The project demonstrated the practical application of theoretical concepts, including API integration, machine learning, and graphical user interface design. It provided a valuable learning experience in software development, data processing, and predictive modeling. By successfully bridging the gap between technical implementation and user-centric design, the project exemplifies the potential of modern technologies in addressing real-world needs.

Looking ahead, future iterations of the project could explore incorporating advanced machine learning techniques, such as deep learning models, to improve prediction accuracy. Additional weather parameters, such as wind direction and UV index, could also be included to broaden the application’s scope. The use of more sophisticated visualization tools and support for multiple APIs could further enhance the application’s functionality and reliability.

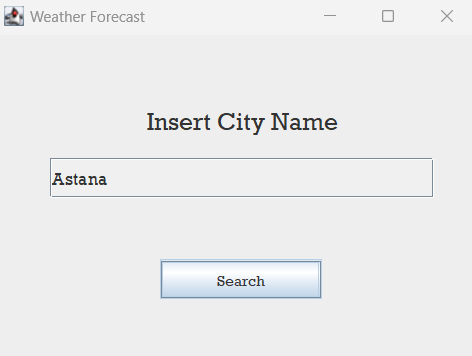
In conclusion, this project achieved its objective of creating a functional, user-friendly weather forecasting application. It underscores the importance of integrating machine learning and intuitive design in software development, offering a foundation for further advancements in weather forecasting systems.

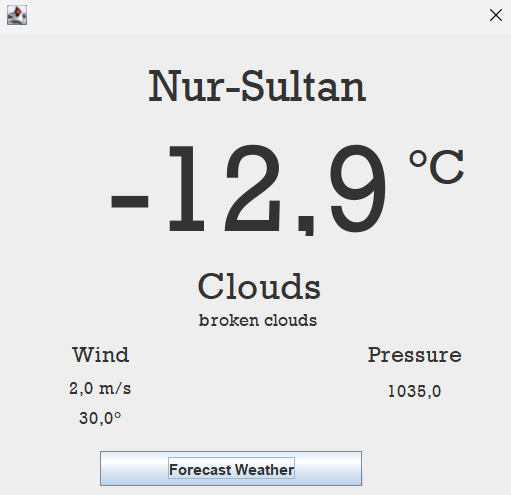
**References**

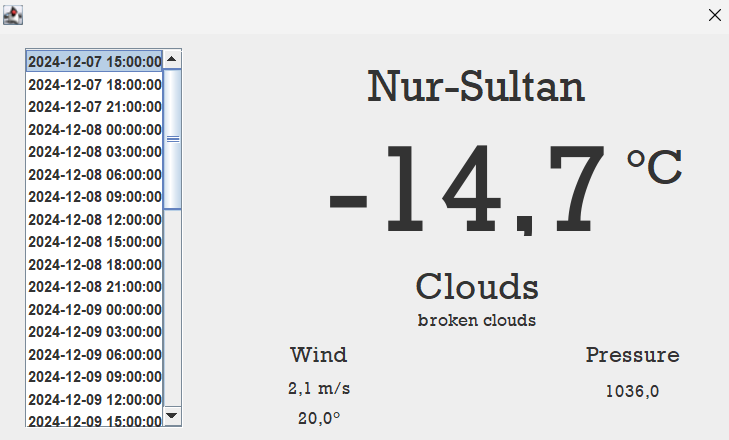
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**Appendices**

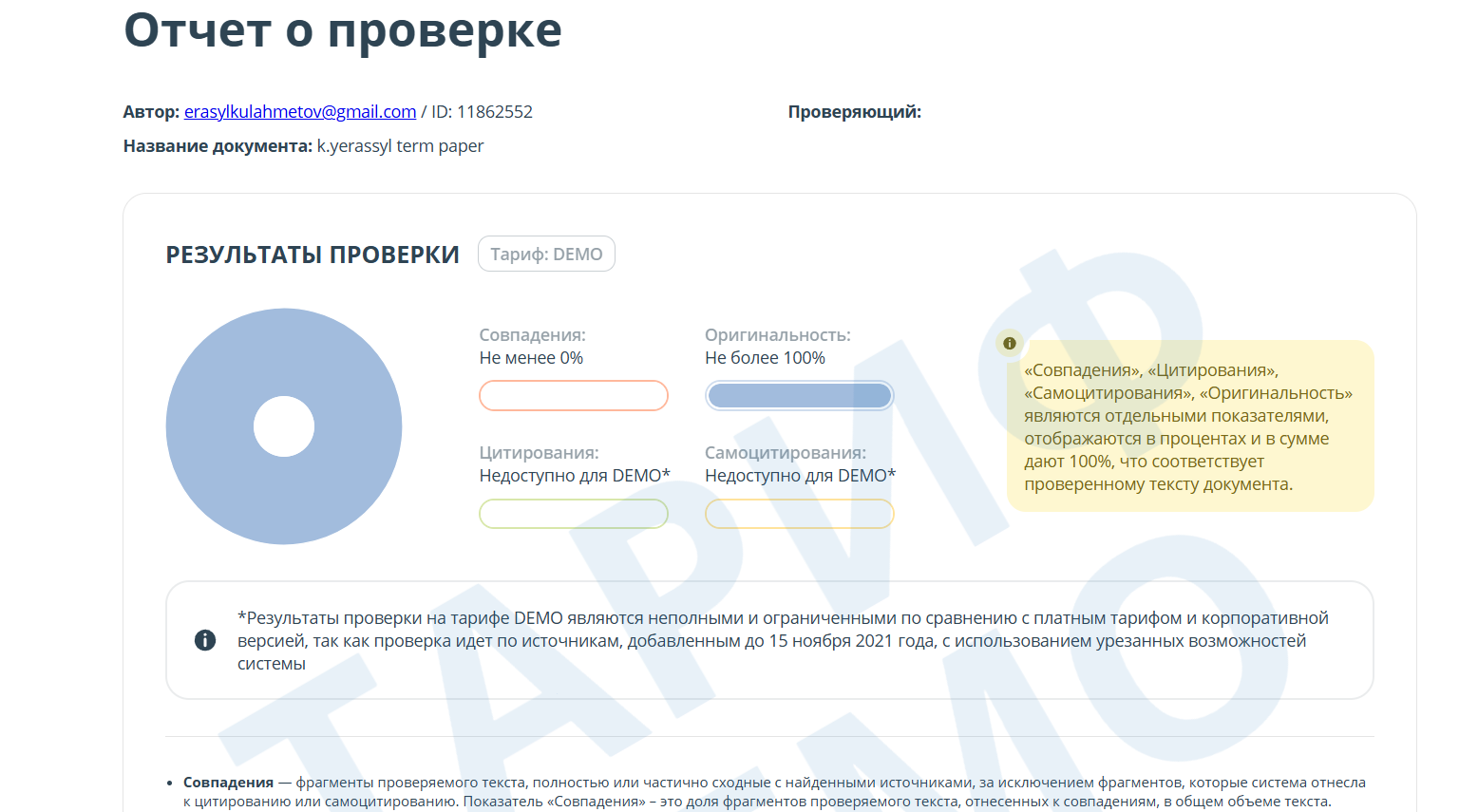
Appendix A. Client Application Pages

**Figure A.1** Main page

**Figure A.2** Additional page

**Figure A.3** Total result page

Appendix B. Originally evaluation outcome

**Figure B.** Plagiarism Analysis