SEMESTER GRADE PREDICTOR

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DEPARTMENT OF COMPUTER SCIENCE

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ABSTRACT

This project centers on leveraging machine learning, specifically the Sequential Model of Artificial Neural Networks, to predict students' semester grades based on their prior academic performance. By analyzing NUML dataset, our aim is to develop a robust predictive tool that enhances educational forecasting. This endeavor bridges the realms of artificial intelligence and education, promising advancements in personalized learning and proactive academic support.

The project employs a systematic approach, leveraging the Sequential Model of Artificial Neural Networks. Initial steps involve data preprocessing, extracting meaningful features from students' historical grades. The model's architecture is then configured to capture intricate patterns in the dataset. Rigorous training and optimization refine the model, ensuring its efficacy in predicting semester grades based on past academic records.

The project rigorously validates predictions through a robust testing framework. Historical academic data is partitioned into training and testing sets, ensuring model generalization. Cross-validation techniques further bolster reliability. Performance metrics such as accuracy and precision gauge the model's effectiveness, providing insights into its real-world applicability and reinforcing its credibility in predicting semester grades with precision.

While the predictive model showcases promising accuracy, it's essential to acknowledge its limitations. The system heavily relies on historical data, potentially neglecting individual variations and external factors. Limited by the available dataset, the model may face challenges in adapting to diverse academic environments. Ongoing research aims to address these constraints, fostering continuous improvement and broader applicability.

CERTIFICATE

Dated: ____________________

Final Approval

It is certified that the project report titled **'Forecasting Semester Grades'** submitted by **Muhammad Nauman Khan, Azan Ahmad,** and **Ahtesham Shakeel** for the partial fulfillment of the requirement of a **"Bachelor's Degree in Computer Science"** is approved.

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DECLARATION

We hereby declare that our dissertation is entirely our work and genuine/original. We understand that in case of discovery of any PLAGIARISM at any stage, our group will be assigned an F (FAIL) grade and it may result in withdrawal of our Bachelor's degree.

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PLAIGRISM CERTIFICATE

This is to certify that the project entitled “**Forecasting Semester Grades**” is being submitted here for the award of the “**Degree of Bachelor” in “Computer Science**”. This is the result of the original work by **Muhammad Nauman Khan, Azan Ahmad,** and **Ahtesham Shakeel** under my supervision and guidance. The work embodied in this project has not been done earlier for the basis of the award of any degree or compatible certificate or similar title this for any other diploma/examining body or university to the best of my knowledge and belief.

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CHAPTER 1
INTRODUCTION

Within the realm of educational data analysis, data mining emerges as a potent tool for unraveling patterns and relationships in extensive datasets. As educational institutions grapple with escalating data volumes, the imperative to predict student outcomes intensifies. This project's motivation stems from the inadequacies of traditional methods in handling the complexity of educational data. By leveraging data mining techniques, particularly in predictive analytics, our final year project seeks to forecast student performance comprehensively. Motivated by the desire to enhance academic support and identify at-risk students, this project aims to demonstrate the efficacy of data mining in optimizing educational pathways. The subsequent sections will delve into the project's methodology, testing, validation, and achievements, providing a thorough exploration of how data mining contributes to predicting student outcomes.

1.1. Motivation

Data mining for student prediction stems from a fundamental desire to enhance the quality and effectiveness of academic support systems. As educational institutions gather vast amounts of data, the need to make sense of this information becomes critical. Traditional methods often struggle to uncover hidden patterns within this data, making it challenging to provide timely interventions and personalized assistance to students. By harnessing the capabilities of data mining, we aim to unlock valuable insights that can significantly improve the accuracy of predicting student outcomes. This motivation is rooted in a commitment to fostering student success, identifying potential challenges early on, and ultimately creating a more responsive and tailored educational experience. Through the application of data mining techniques, we aspire to empower educational stakeholders with actionable information, facilitating informed decision-making and, ultimately, contributing to the overall improvement of the learning environment.

1.2. Problem Identification

In the realm of education, the increasing volume of data presents a challenge in effectively utilizing this information for the benefit of students and institutions alike. Traditional methods of result prediction often fall short in capturing the intricate patterns and dependencies within academic data. This gap highlights the need for a more sophisticated approach, particularly in the context of predicting students' results. The problem lies in the limitations of current methodologies to extract meaningful insights from the wealth of available educational data. Data mining, as a solution, offers the potential to address this problem by leveraging advanced algorithms to sift through complex datasets. The challenge is to implement data mining techniques effectively, ensuring that the resulting predictive models not only provide accurate forecasts of student outcomes but also contribute to a more proactive and personalized educational support system. This problem statement underscores the importance of developing robust data mining strategies to navigate the complexities of educational data and enhance the precision of student result predictions.

1.3. Goals and Objectives

Some of the promising objectives of the system are as follows:

- Develop a robust data mining framework capable of analyzing complex educational datasets and identifying crucial patterns for accurate result predictions.
- Implement predictive models using insights from the framework to forecast students' academic performance across multiple semesters, continuously refining them for improved accuracy.
- Integrate predictive models into educational systems to enable timely interventions for at-risk students and utilize data-driven insights to inform curriculum development, teaching strategies, and resource allocation, ultimately fostering improved student outcomes.

1.4. Nature of Project

Our project primarily falls under the domain of Machine Learning, specifically focusing on predictive analytics for student outcomes in the education sector. Leveraging advanced algorithms and models, including Artificial Neural Networks (ANN) we delve into the intricate patterns and dependencies within academic data to forecast students' results from the 1st to the 8th semester. The project utilizes the power of neural networks, making it inherently AI-driven, to enhance the accuracy and adaptability of predictions. While the core nature revolves around Machine Learning, the methodologies employed encompass aspects of Data Mining, ensuring a comprehensive exploration of educational datasets. This interdisciplinary approach positions our project at the intersection of AI, Machine Learning, and Data Mining, emphasizing its significance in advancing predictive analytics for educational insights.

- ANN Model

1.5. ANN Model

Here's how ANNs could be applied to predict student results.

1.5.1. Input Layer

The input layer of the neural network would consist of nodes representing the features or attributes of the student's previous semester(s). For example, these features could include grades in different subjects, attendance records, participation in extracurricular activities, etc.

1.5.2. Hidden Layers

Between the input and output layers, there can be one or more hidden layers. Each hidden layer consists of nodes that perform mathematical operations on the input data. These layers enable the network to learn complex patterns and relationships within the data.

1.5.3. Output Layer

The output layer produces the predicted result, which in this case would be the student's performance in the upcoming semester(s). The output layer could consist of a single node for regression tasks (predicting a continuous value, like Percentage %) or multiple nodes for classification tasks.

1.5.4. Training process

During the training process, the neural network learns to make accurate predictions by adjusting the weights of connections between nodes based on the error between the predicted output and the actual result. This is typically done using optimization algorithms like gradient descent.

1.5.4. Evaluation and Prediction

Once trained, the neural network can be used to predict a student's performance in future semesters based on their previous academic data. The model takes in the features representing the student's previous semester(s) and outputs the predicted result for the upcoming semester(s).

1.6. Organization of Report

The report on our final year project concerning the analysis and forecasting of student semester grades utilizing the NUML dataset is structured into seven distinct chapters, each focusing on different aspects of our project.

Chapter 1, the "Introduction," provides a comprehensive overview of the project's objectives and outlines the anticipated successes the system aims to achieve.

Chapter 2, titled "Background and Existing Work," we delve into the necessity of the system and conduct a comparative analysis with alternative methods to highlight its advantages and unique features.

Chapter 3, "Requirements Specification," delves into the detailed breakdown of the project's modules and delineates the non-functional requirements crucial for optimal system operation.

Chapter 4, "System Modeling," thoroughly explains the structure and flow of the proposed system through a variety of visual aids such as class, sequence, architecture, and activity diagrams.

Chapter 5, "Implementation," introduces the practical aspects of our project, providing a detailed explanation of the useful components of our strategy and its application.

In Chapter 6, "Testing, Analysis, and Validation," we employ test cases to evaluate the efficiency and reliability of our system.

Finally, Chapter 7, "Conclusion and Future Work," summarizes the project's accomplishments, discusses any limitations, and suggests possible directions for future improvements and developments.

CHAPTER 2

BACKGROUND AND EXISTING SYSTEMS

In the dynamic landscape of education, the influx of data has transformed how institutions operate, making information-driven decision-making essential. The challenges of traditional educational methodologies in handling and extracting valuable insights from this data have spurred the need for innovative approaches. Our project emerges against this backdrop, with a focus on leveraging machine learning to predict student outcomes. As educational data continues to grow in complexity, the adoption of advanced techniques becomes imperative for meaningful analysis and informed interventions.

Several efforts have been made to address the complexities of educational data analysis. Current systems often rely on statistical methods or rudimentary algorithms for student result predictions. However, the limitations of these approaches are evident in their inability to capture the nuanced relationships within academic datasets. Past initiatives have laid the groundwork for incorporating machine learning into education, but gaps remain in achieving precise and adaptive predictions. Our project aims to build upon and extend the existing body of work by harnessing the power of machine learning and data mining to create a more sophisticated and effective predictive system for student outcomes. The following sections delve into the specific motivations, goals, and methodologies that underpin our novel approach, contributing to the on-going evolution of predictive analytics in education.

2.1. Existing Systems

In their study [1], Patel, Shah, Thakkar, and Kotecha explored the prediction of stock and stock price index movements in Indian stock markets using machine learning techniques. They compared the performance of four prediction models - Artificial Neural Network (ANN), Support Vector Machine (SVM), random forest, and naive-Bayes - with a focus on data preprocessing to improve prediction accuracy.

In their systematic literature review [2], Albreiki, Zaki, and Alashwal explored the application of machine learning techniques in predicting student performance and dropout rates in academic institutions. They reviewed relevant literature from 2009 to 2021 and highlighted the use of machine learning methods to address challenges in evaluating student performance and implementing intervention plans.

In the study [3], Pallathadka et al. explored the classification and prediction of student performance data using different machine learning algorithms. The authors investigated the application of techniques such as Nave Bayes, ID3, C4.5, and SVM on the UCI machinery student performance dataset. The study aimed to assist educational institutions in forecasting student performance and implementing strategies to enhance academic achievement.

This study [4] presents a systematic literature review focusing on machine learning algorithms used in predicting student academic performance. A total of 2700 articles were initially considered, and 56 were filtered for further analysis. Features utilized, databases, algorithms, and future directions were examined. The study concludes that machine learning techniques effectively predict student performance based on specified features, offering benefits for students and academic institutions. However, challenges remain, and more studies are needed to refine and generalize results. The paper provides valuable insights and future guidelines for practitioners and researchers in educational data mining.

In the article [5], Ouatik et al. present a system utilizing big data and machine learning algorithms to predict academic success based on various student factors and activities. Employing methods such as KNN, C4.5, and SVM, alongside big data technologies like HDFS and MapReduce, the system enhances prediction efficiency and execution time. Results indicate a recognition rate of 87.32% using SVM. The study contributes to the ongoing effort to improve student success prediction in educational settings.

In the literature review [6], Rastrollo-Guerrero, Gómez-Pulido, and Durán-Domínguez (2020) emphasize the importance of predicting students' performance for educational institutions to design effective interventions and support mechanisms. Data mining techniques, including Machine Learning, Collaborative Filtering, Recommender Systems, and Artificial Neural Networks, are highlighted for their crucial role in analyzing and processing data to predict students' academic outcomes and identify dropout risks. The study provides an extensive review of modern techniques and algorithms applied in this field, aiming to enhance understanding and improve educational practices.

In their research [7], Altabrawee, Abdul Jaleel Ali, and Qaisar Ajmi (2019) highlight the importance of predicting students' performance for educational institutions to provide effective support and enhance learning outcomes. The study employs four machine learning techniques - Artificial Neural Network, Naïve Bayes, Decision Tree, and Logistic Regression - to predict students' performance in a computer science subject. Unique features such as internet usage for learning and time spent on social networks are considered. The research compares model performance using the ROC index and analyzes factors influencing student performance.

In contemporary society [8], assessing student performance holds significant importance. The application of machine learning algorithms has witnessed substantial growth across various domains, including predicting student performance. This study aims to enhance the prediction of students' performance utilizing machine learning algorithms and ensemble techniques. Four algorithms - Decision Tree, Naïve Bayesian, K-Nearest Neighbors, and Extra Tree - were applied to a dataset consisting of 1000 instances and 22 attributes. Ensemble methods such as Bagging and Boosting were employed to amalgamate the results of individual learners. The study compared the performance of different techniques based on factors like accuracy, sensitivity, specificity, and F1-score, concluding that Bagging yielded the best results. The developed model holds potential in predicting students' performance in selected courses, thereby benefiting both students and institutions.

2.2. Comparison of Existing Systems

Nine articles have their contributions and methodologies presented in the tabular form that follows, which represents the summary of the evaluated literature, as shown in Table 2.1.

Table 2.1: Comparison of Existing Systems

Ref.	Year	Author	Approach	Contribution	Limitations
[1]	2014	P. J. Shah, S. Thakkar and P. &. Kotecha	Artificial Neural Network (ANN), Support Vector Machine (SVM), random forest, and naive-Bayes	prediction of stock and stock price index movements in Indian stock markets	Performance varies for each Algorithm
[2]	2021	B. Albreiki, N. Zaki and H. Alashwal	machine learning techniques	student performance and dropout rates in academic institutions	challenges in evaluating student performance and implementing intervention plans.

[3]	2021	H. Pallathadka, A. Wenda, E. Ramirez-Asís, M. Asís-López, . J. Flores-Albornoz and . K. Phasinam	Nave Bayes, ID3, C4.5, and SVM	assist educational institutions in forecasting student performance	explored the classification and prediction of student performance
[4]	2021	r. Balaji , S. Alelyani , A. Qahmash and M. Mohana	focusing on machine learning algorithms	machine learning techniques effectively predict student performance based on specified features	Challenges remains, and more studies are needed to refine and generalize results
[5]	2022	F. Ouatik, M. Erritali, F. Ouatik and M. Jourhmane	KNN, C4.5, and SVM	Results indicate a recognition rate of 87.32% using SVM	Challenges faced, accuracy rate varies for different Algorithms
[6]	2020	R. Guerrero, G. Pulido and D. Domínguez	Data mining techniques, including Machine Learning, Collaborative Filtering, Recommender Systems, and Artificial Neural Networks	Predict students' academic outcomes and identify dropout risks.	Challenges remains, and more studies are needed to refine and generalize results
[7]	2019	Altabrawee, A. J. Ali and Q. Ajmi	Artificial Neural Network, Naïve Bayes, Decision Tree, and Logistic Regression	Predict students' performance in a computer science subject	Performance analyzed only for Computer Science Subject
[8]	2020	R. Singh and S. Pal	Decision Tree, Naïve Bayesian, K-Nearest Neighbors, and Extra Tree	Bagging and Boosting were employed to amalgamate the results of individual learners	Limiting the generalizability of the findings to broader student populations or diverse academic contexts.

2.3. Summary

Overall, these research and applications show how mobile technology and artificial intelligence may be used to better manage rice crops and combat illness. However, the farmers in Pakistan cannot use practically any of these. Unfortunately, farmers have a relatively low literacy rate. Therefore, we must take care to create a program that is simple to use, requires little training, has a user-friendly interface, and produces accurate results.

In essence, Chapter 2 offers a comprehensive review of the detection of rice leaf disease, its challenges, and the current status of the field, which makes it a crucial place to start for the final year report.

CHAPTER 3

REQUIREMENTS SPECIFICATION

The success of any predictive modeling project hinges on a well-defined set of system requirements and specifications. In the context of our grade prediction project, establishing these parameters is crucial to ensure the effective development, implementation, and deployment of the predictive model.

This section outlines the hardware, software, and data requirements essential for the seamless functioning of the grade prediction system. Additionally, we detail the specifications that govern the design and development of the predictive model, ensuring accuracy, reliability, and scalability.

By delineating the system requirements and specifications, we aim to provide a comprehensive foundation for stakeholders, developers, and researchers involved in or interested in the grade prediction process. This transparency facilitates a deeper understanding of the technical framework supporting our project and sets the stage for the subsequent sections of the report.

The forthcoming discussion will delve into the specific hardware configurations, software tools, and dataset characteristics, shedding light on the intricacies of our approach. The adherence to these outlined requirements ensures a robust and adaptable system capable of meeting the dynamic challenges posed by the diverse academic scenarios encountered in the grade prediction process.

3.1. System Specification

The successful development and deployment of a grade prediction system hinge upon a thorough delineation of system specifications. This section of the report delves into a comprehensive exploration of the intricacies surrounding hardware, software, and dataset specifications, collectively forming the foundational elements that underpin the robustness of our predictive model. By thoroughly examining and detailing these specifications, we aim to provide a nuanced understanding of the essential components that contribute to the efficacy and reliability of the grade prediction system, ensuring a holistic comprehension of its technical architecture and operational framework.

3.1.1. Hardware Specification

Our grade prediction system demands a robust hardware infrastructure to handle the computational requirements of training and deploying machine learning models. The system's hardware specifications include processor capabilities, memory requirements, and any specialized hardware accelerators employed to optimize model performance, as shown in Table 3.1.

Table 3.1: Hardware Specification

Core	Generation	RAM
i5 (min)	5^{th} (min)	8GB

3.1.2. Software Specification

The software environment in which our predictive model operates is a critical determinant of its functionality. This section outlines the software tools, libraries, and frameworks employed in the development process. We detail the programming languages chosen, machine learning libraries utilized, and any additional software components contributing to the seamless functioning of the system, as shown in Table 3.2.

Table 3.2: Software Specification

Tool	Programming Language	ML Model
Jupyter Notebook	Python	ANN

3.1.3. Database Specification

The quality and comprehensiveness of the dataset are pivotal to the accuracy of our grade prediction model. Here, we describe the characteristics of the dataset used, including the number of samples, features, and any pre-processing steps applied. Additionally, we address data privacy and ethical considerations integral to handling student-related information, as shown in Table 3.3.

Table 3.3: Database Specification

Data Format	Records	Training Data	Testing Data
Excel File (.xlsx)	2000	1600	400

3.2. Use Case Model

The project revolves around the fundamental process of utilizing historical student performance data to predict future grades accurately. The absence of a front-end interface positions the emphasis on the backend operations, particularly data processing, algorithm implementation, and model evaluation.

3.2.1. Data Collection

The project initiates with the collection of student academic data, primarily focusing on past semester marks. The dataset serves as the foundation for training and validating the predictive model.

3.2.2. Data Cleaning and Preprocessing

Data cleaning is crucial to ensure the accuracy and reliability of the model. This involves handling missing values, addressing outliers, and standardizing data formats. Following cleaning, the data undergoes preprocessing, including feature scaling and encoding categorical variables.

3.2.3. Model Training

A machine learning model is trained using the preprocessed dataset. The choice of the algorithm depends on the nature of the data and the desired predictive outcome. The training phase involves fine-tuning the model to enhance its accuracy and generalizability.

3.2.4. Prediction

Once the model is trained, it is employed to make predictions on new data instances. In the context of this research, the focus is on predicting student grades for upcoming semesters based on historical academic performance.

3.2.5. Result Analysis

The predictions are then analyzed, and the model's performance is evaluated. This involves assessing the accuracy, precision, and recall of the model to determine its effectiveness in predicting student grades.

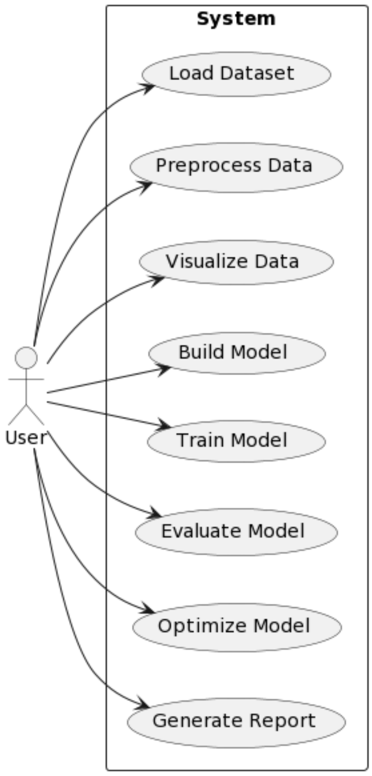

Figure 3.1: Use Case Model

3.3. Use Cases

The use case model outlines the core functionalities of a research-based project, devoid of a user interface. It encompasses systematic data collection, specifically targeting students' marks from diverse sources. Following data collection, a critical phase of data cleaning and preprocessing ensures data quality and prepares it for machine learning model training. The subsequent model training step involves the selection of a suitable algorithm and parameter tuning for optimal performance. The trained model is then utilized for predicting student grades based on input data, with the final use case focusing on result analysis. This involves evaluating prediction effectiveness through metrics like accuracy and precision. The model's end-to-end process prioritizes data processing, machine learning, and analysis in the absence of a dedicated user interface.

3.3.1. Data Cleaning and Preprocessing

. This use case focuses on ensuring the quality and reliability of the collected data. It includes processes such as handling missing values, addressing outliers, and standardizing data formats to prepare the dataset for subsequent model training., as shown in Table 3.4.

Table 3.4: Data Cleaning and Preprocessing – Full Dress Use Case

Use Case Name:	**Data Cleaning and Preprocessing**
Actors:	Researcher
Summary:	The collected data will be check and will be cleaned to perform model training.
Preconditions:	- The researcher must have knowledge of Data Cleaning libraries.
Main Flow:	- The data will be checked for errors, null values, and duplicates. - The preprocessing will be done to get the required data for model training.
Alternative Flows:	- The researcher can use alternative libraries in case of any difficulty.
Post conditions:	The data is cleaned and preprocess, which is now ready for model training.

3.3.2. Prediction

The prediction use case focuses on utilizing the trained machine learning model to predict student grades for upcoming semesters. It involves receiving prediction requests, obtaining input data, making predictions, and making the results available for analysis., as shown in Table 3.5.

Table 3.5: Prediction – Full Dress Use Case

Use Case Name:	**Prediction**
Actors:	Researcher
Summary:	The researched provides the testing data to the model to perform the predictions.
Preconditions:	- Make sure the libraries are imported and model is trained perfectly.

Main Flow:	-Import the required libraries and provide the testing data to the model to perform predictions.
Alternative Flows:	- The model is not trained accurately and is unable to perform the prediction.
Post conditions:	- The result is predicted based on the testing data.

3.4. Non-Functional Requirements

Non-functional requirements outline the qualities and characteristics that contribute to its overall performance, reliability, and user satisfaction. In this section, we detail the non-functional requirements that guide the development and operation of our grade prediction system.

3.4.1. Performance

The system must handle a minimum of 2000 student records for efficient data processing.

3.4.2. Reliability

Predictions must maintain an accuracy level of 80% to develop confidence in users.

3.4.3. Scalability

The system must scale horizontally to accommodate an increase in the number of concurrent users. The model training process must scale with the growing volume of historical data.

3.6. Project Feasibility

A thorough examination of feasibility is crucial to establish the viability and potential success of the project aimed at predicting semester grades. This comprehensive analysis spans across diverse dimensions, including but not limited to technical, economic, legal, operational, and scheduling aspects. Each facet contributes valuable insights into the project's overall feasibility. The primary objective is to assess whether the project aligns seamlessly with organizational goals, ensuring its technical feasibility, and evaluating its ability to be completed within the specified constraints. This multifaceted analysis forms a foundational step in the decision-making process, providing a nuanced understanding of the project's prospects and challenges across various domains.

3.6.1. Technical Feasibility

The examination of technical feasibility delves into an in-depth evaluation of the organization's capacity to effectively implement the requisite technologies essential for the successful establishment of the grade prediction system. This comprehensive study encompasses a thorough assessment of various factors, including but not limited to the availability of skilled personnel proficient in the relevant technologies, the existing technology infrastructure, and a meticulous evaluation of the feasibility surrounding the integration of necessary software and hardware components. The aim is to ascertain the organization's readiness and ability to embrace the technological requirements inherent in the grade prediction project, ensuring a seamless and efficient implementation process.

3.6.2. Economic Feasibility

The economic feasibility examination represents a comprehensive evaluation of the financial viability inherent in the project. This evaluative process extends to a meticulous scrutiny of the various costs associated with the project, encompassing expenditures related to hardware acquisition, software implementation, human resource allocation, training initiatives, and sustained maintenance efforts. A pivotal component of this analysis involves the execution of a thorough cost-benefit analysis, wherein a nuanced comparison is made to discern whether the anticipated benefits derived from the project surpass and justify the overall costs incurred. This thorough economic feasibility study plays a crucial role in illuminating the financial aspects of the project, aiding stakeholders in making informed decisions regarding its continued viability and potential economic impact.

3.6.3. Legal Feasibility

The assessment of legal feasibility involves a comprehensive examination to ascertain the project's adherence to prevailing laws and regulations. This entails a meticulous review of various legal aspects, such as compliance with data privacy laws, considerations pertaining to intellectual property rights, and a thorough evaluation of any legal constraints that may potentially influence the developmental and deployment phases of the grade prediction system. By taking into account these multifaceted legal considerations, the study aims to ensure that the project aligns seamlessly with the legal landscape, fostering a framework that not only complies with existing regulations but also safeguards against potential legal challenges throughout the lifecycle of the system.

3.6.4. Operational Feasibility

The operational feasibility analysis serves as a comprehensive examination of the seamless integration of the proposed system with the organization's existing processes and operational framework. This evaluative process encompasses a thorough consideration of diverse factors, including but not limited to user acceptance levels, the requisite training needs, and an in-depth assessment of the potential impact on day-to-day operations. By delving into these multifaceted operational considerations, the study aims to gauge the extent to which the proposed system aligns harmoniously with established processes, fostering a thorough understanding of its feasibility and the potential optimizations it can bring to the organization's daily functioning.

3.6.5. Scheduling Feasibility

The investigation into scheduling feasibility entails a comprehensive assessment of the project's capacity to be successfully concluded within the specified time constraints. This evaluative process encompasses a detailed scrutiny of various elements, including the development timeline, the identification and monitoring of crucial milestones, and a thorough examination of potential risks that have the potential to impact the project schedule. By delving into these multifaceted scheduling considerations, the study aims to ascertain the project's temporal feasibility, providing insights into its capacity to adhere to predefined timelines and anticipate and mitigate potential challenges that may arise during the course of its development and implementation.

3.7. Summary

The grade prediction project aims to develop a robust system capable of forecasting student grades based on historical academic data. The project's foundation lies in a comprehensive analysis, starting with system requirements and specifications that define the technical landscape. The modular system architecture incorporates key functionalities such as data ingestion, model training, predictions, and reporting.

Both functional and non-functional requirements establish clear expectations for system performance, scalability, security, usability, and maintainability. Resource requirements outline the hardware, software, and human resources necessary for successful development, deployment, and on-going operation. The feasibility analysis covers technical, economic, legal, operational, and scheduling aspects, ensuring a thorough examination of the project's viability.

CHAPTER 4

SYSTEM MODELLING

System modelling serves as a pivotal phase in the development lifecycle, providing a structured approach to represent and visualize the various components, processes, and interactions within a complex system. It offers a systematic means of transforming abstract concepts into tangible representations, aiding in the comprehension, design, and refinement of the grade prediction system. By employing various modelling techniques, we aim to elucidate the system's architecture, data flow, and relationships, fostering a deeper understanding among stakeholders. This chapter delves into the intricacies of system modelling, shedding light on the methodologies and visualizations employed to conceptualize, design, and refine the components of our grade prediction project. Through systematic modelling, we endeavor to enhance clarity, facilitate communication, and pave the way for effective implementation and optimization of the grade prediction system.

4.1. System Design

In the realm of system modeling, the phase of "System Design" holds paramount significance, serving as the cornerstone for the conceptualization and structuring of our grade prediction system. This section ventures into the intricate process of designing the system architecture, elucidating the methodologies, decisions, and considerations that contribute to the formulation of a coherent and efficient framework. System design involves translating the requirements and specifications outlined in earlier chapters into tangible components, relationships, and data flows. As we embark on this journey, the overarching goal is to craft a design that not only accommodates the technical intricacies of machine learning and data processing but also aligns seamlessly with the overarching objectives of accurate grade prediction and user-centric functionality. Through the exploration of system design principles, we aim to provide a comprehensive understanding of the decisions made, the design choices undertaken, and the rationale behind shaping the architecture of our grade prediction system.

4.2. Design Approach

In the realm of system design, the chosen approach plays a pivotal role in shaping the architecture of our grade prediction system. The design approach encompasses a strategic framework that guides the decision-making process, influencing the organization, structure, and interplay of system components. This section delves into the fundamental principles and methodologies guiding our design approach, laying the groundwork for a cohesive, scalable, and efficient system.

4.3. Interface Design

The primary objective of the Semester Grade Predictor web application is to present graphical representations and correlation analyses. Additionally, the platform aims to provide an overview of the total number of enrolled students, along with detailed semester-wise data. It facilitates the comparison between actual and predicted results for each semester, offering valuable insights into academic performance trends. Furthermore, the application delves into statistical metrics such as Mean Square Error, providing a quantitative measure of prediction accuracy. This initiative serves as a significant component of the final year project, contributing to the understanding and application of predictive analytics in the educational domain.

4.3.1. Splash Screen

The following interface displays a splash screen containing fields for name, login, and a button. When clicked, the button redirects the response to another page, which serves as the main page of the web app. The splash screen is automatically loaded when the server initializes to enhance the interactive user experience, as shown in Figure 4.1.

Figure 4.1: Splash Screen

4.3.2. Data Cleaning

The interface also features a "Data" button, providing access to the analytics dashboard. Within this dashboard, users can access comprehensive insights, including data on 2000 total students across 8 semesters. The dashboard presents correlation graphs and data cleaning visualizations, offering users a detailed understanding of the underlying data structure and relationships. This comprehensive display empowers users to make informed decisions and extract valuable insights from the available dataset, as shown in Figure 4.2.

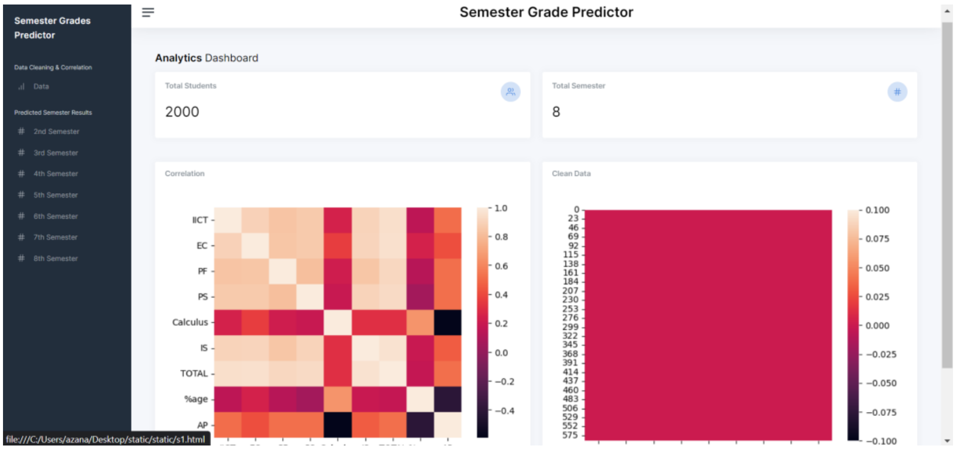

Figure 4.2: Data Cleaning

4.3.3. Result Visualization

The interface incorporates a specific button labeled "2nd Semester," granting user’s access to the analytics dashboard tailored specifically for this semester. Within this dashboard, users can observe analytics pertinent to the second semester of the academic program. The dashboard displays data indicating a total of 2000 students and presents a comparison of actual versus predicted values, accompanied by the Mean Square Error metric. Additionally, users have the option to navigate to analytics dashboards for other semesters, ranging from the 2nd to the 8th semester, through buttons conveniently located on the left side of the interface. This consistent layout ensures ease of navigation and facilitates comprehensive analysis across all semesters of the academic program, as shown in Figure 4.3.

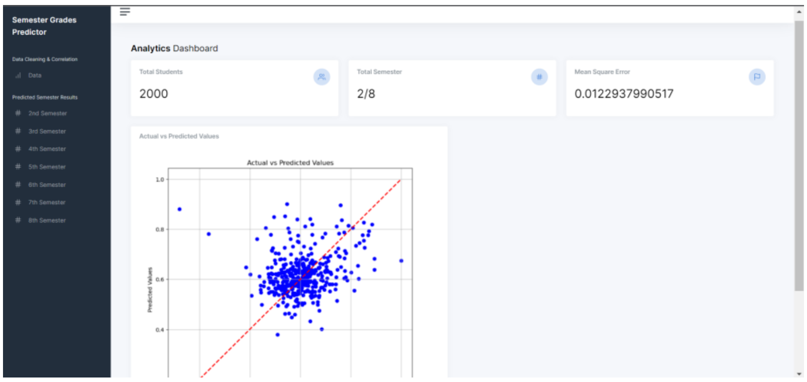

Figure 4.3: Result Visualization

4.4. View Model of Architecture

The View Model of Architecture in system modeling refers to the representation of the system's architecture from multiple perspectives or views. Each view provides a unique way of visualizing and understanding different aspects of the system, facilitating communication and comprehension among stakeholders. In the context of grade-prediction project, the View Model of Architecture may encompass various views, such as structural, behavioral, and deployment views, each offering insights into different dimensions of the system's design and functionality.

4.4.1. Logical View

The Logical View, as a subset of the View Model of Architecture, focuses on depicting the key abstractions and relationships within the system from a functional perspective. It emphasizes the organization of components, modules, and their interactions without being concerned with the physical deployment or implementation details. In the context of grade prediction system, the Logical View provides a high-level overview of the functional modules, entities, and their interconnections that contribute to the overall system behavior. This section of the system modeling chapter delves into the logical organization of the grade prediction system, illustrating how different components collaborate to achieve the intended functionality.

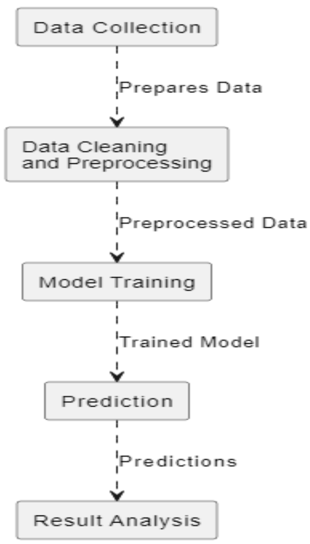

Figure 4.4: Logical View

4.4.2. Process View

The Process View in system modeling provides insights into the dynamic aspects of a system by illustrating how processes, tasks, and activities interact and collaborate to achieve the system's functionality. This view is particularly important for understanding the runtime behavior, performance, and synchronization of processes within the system. The Process View can be employed to depict the flow of activities related to data collection, cleaning, model training, prediction, and result analysis. This view aids in understanding the sequence of actions and the concurrent or sequential nature of processes within the system.

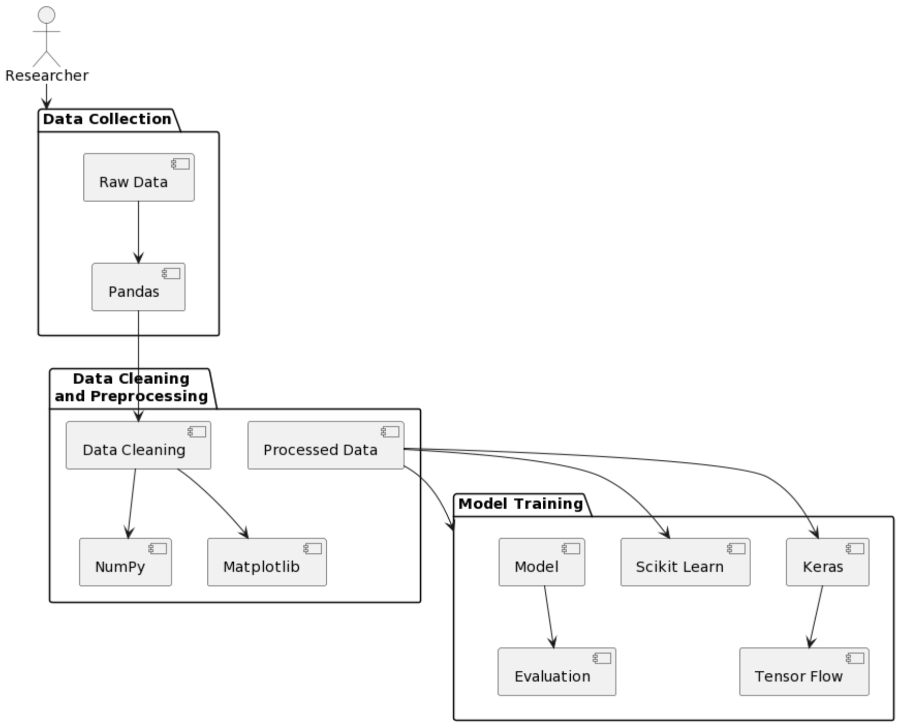

Figure 4.5: Process View

4.4.3. State Diagram

A State Diagram, also known as a State Machine Diagram, is a visual representation that depicts the various states a system or an object can exist in and the transitions between those states. This diagram is particularly useful for modeling the behavior of a system over time and in response to different events or stimuli. A State Diagram can be employed to illustrate the different states a student's grade prediction system might go through during its lifecycle. States could include "Idle," "Data Collection," "Training Model," "Prediction," and more. Transitions between states could be triggered by specific events or conditions, such as the completion of data collection or the successful training of the machine learning model.

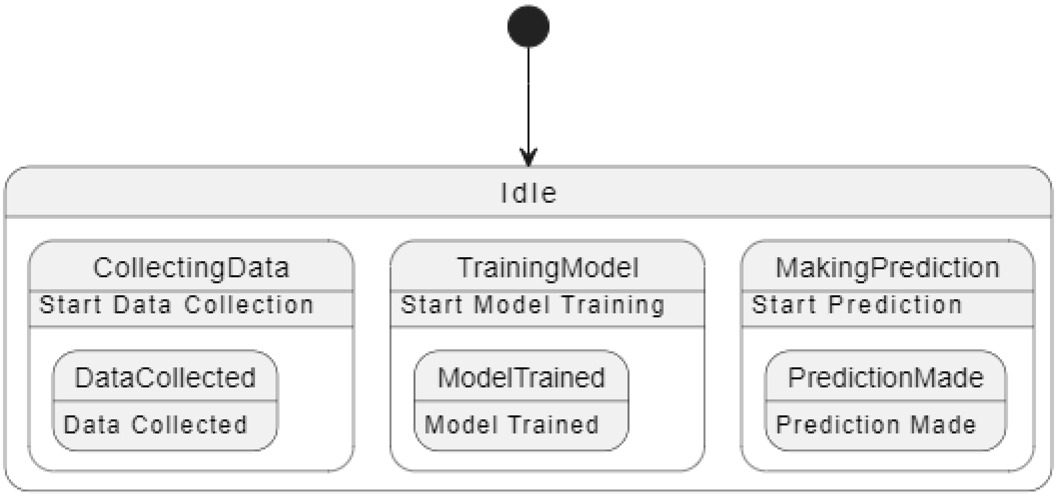

Figure 4.6: State Diagram

4.4.4. System Sequence Diagram

The System Sequence Diagram (SSD) for our Semester Grade Predictor project offers a concise visual representation illustrating the interaction between external actors and the system, depicting the sequential exchange of messages within various use cases or scenarios. As depicted in Figure 4.7, the SSD encompasses all facets of this interaction.

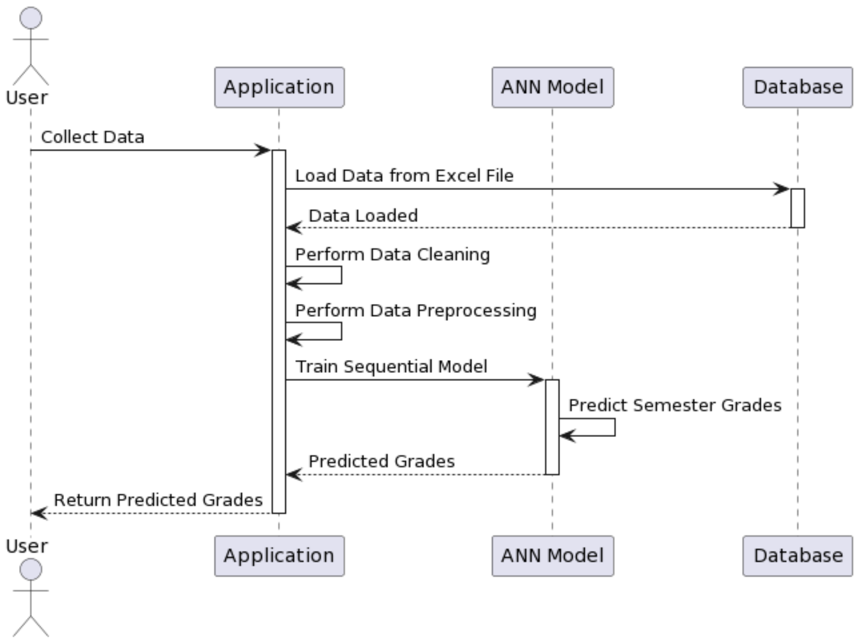

Figure 4.7: System Sequence Diagram

4.4.5. Sequence Diagram

The Semester Grade Predictor project employs sequence diagrams to visually represent the dynamic exchanges among its components during key operations, including Data Collection, data cleaning, preprocessing, model training and prediction. This graphical representation offers insights into the system's dynamic behavior by showcasing the sequential communication between the database, machine learning algorithms, application and user, as depicted in Figure 4.8.

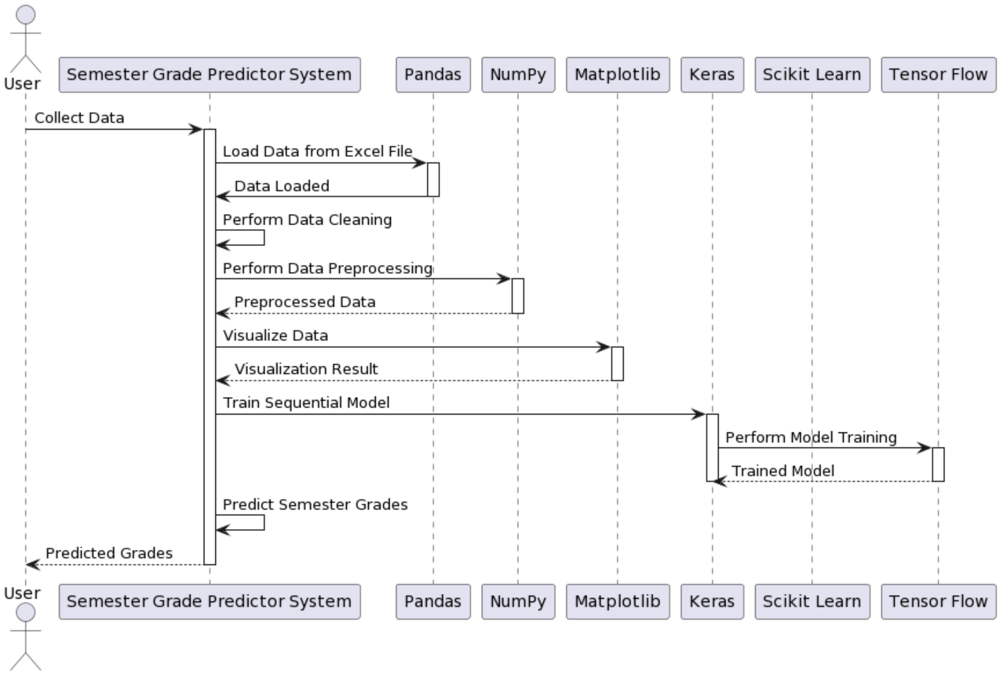

Figure 4.8: Sequence Diagram

4.5. Data Flow Diagram

A Data Flow Diagram (DFD) is a graphical representation that illustrates the flow of data within a system and the processes that transform that data. It provides a comprehensive view of how data moves through various components of a system, including inputs, processes, data stores, and outputs. The primary objective of a DFD is to depict the interactions and dependencies between different elements in the system, offering a high-level abstraction of the system's data flow architecture. In a DFD, processes are represented as circles, data stores as rectangles, data flow as arrows, and external entities as squares. The arrows indicate the direction of data flow, and each process is associated with a specific function or transformation applied to the incoming data. The simplicity and clarity of a DFD make it an effective tool for understanding the data-centric aspects of a system without delving into intricate details. For a grade prediction system, a DFD might showcase processes such as data collection, data cleaning and preprocessing, model training, prediction, result analysis, and the associated data flow between these processes.

4.5.1. DFD Level-0

The level-0 diagram serves to depict the system's fundamental structure, usually featuring a singular process. Meanwhile, the Context diagram offers a holistic view of the system, illustrating the connections between its processes and external entities. It also highlights the principal inputs and outputs of the system, as shown in Figure 4.9.

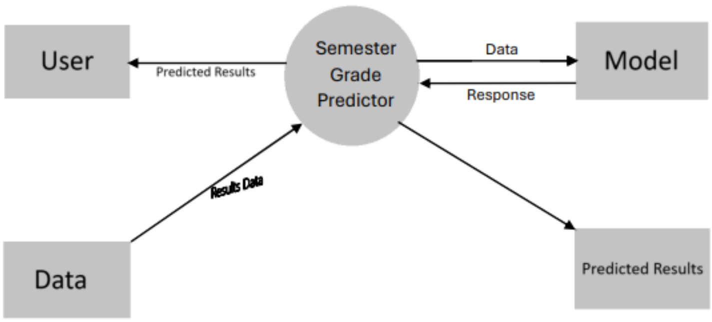

Figure 4.9: Data Flow Diagram Level-0

4.5.2. DFD Level-1

In the Level-1 DFD of the Predictor Semester Grades, the project is segmented into more specialized modules, each delineating its distinct functionalities. These modules are depicted along with the corresponding data flows between them, showcasing the intricate interplay within the system. Figure 4.10 displays a visual representation of the Level-1 DFD, elucidating the inner workings and interactions of the app's components.

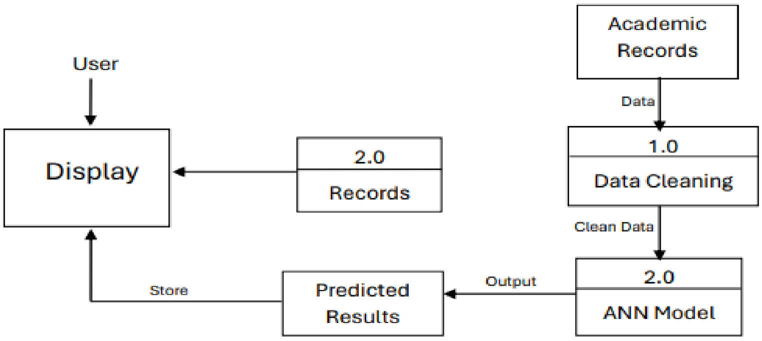

Figure 4.10: Data Flow Diagram Level-1

4.6. Summary

In the System Modeling chapter, we delved into the intricate process of designing and representing the grade prediction system. The chapter commenced with an exploration of the Logical View, emphasizing the structural and behavioral aspects of the system through the use of UML diagrams, including class diagrams and sequence diagrams.The System Design section illuminated the intricacies of designing a cohesive and scalable system. We navigated through the Component-Level Design, breaking down the system into manageable modules with defined interactions and responsibilities. Class diagrams played a pivotal role in illustrating the internal structure of each component, encapsulating attributes and methods. The Behavioral View section showcased the dynamic aspects of the system through various behavioral diagrams, such as Sequence Diagrams and Collaboration Diagrams. These diagrams provided a comprehensive understanding of the interactions between system components, emphasizing the flow of activities and messages. The exploration extended to the construction of a Data Flow Diagram (DFD) Level-0, offering a high-level overview of the major processes and data flows within the grade prediction system. The DFD depicted the flow of data through essential processes like Data Collection, Data Cleaning and Preprocessing, Model Training, Prediction, and Result Analysis. Lastly, the chapter concluded with the design and representation of the Component-Level Design, capturing the internal workings of each module and their interconnections. The use of class diagrams facilitated a detailed blueprint for the internal design of the system. In essence, the System Modeling chapter provided a holistic perspective on designing, visualizing, and understanding the intricacies of the grade prediction system. Each modeling tool and technique employed contributed to a comprehensive and insightful representation of the system's structure and behavior.

CHAPTER 5

IMPLEMENTATION

The implementation phase of our project marks a pivotal stage where theoretical concepts seamlessly transition into practical application. In this section, we delve into the intricate details of how we harnessed the power of Python and its robust libraries—namely, Pandas, NumPy, Matplotlib, and TensorFlow—to turn raw data into valuable insights. Through meticulous data cleaning and utilization of advanced machine learning techniques, we not only prepared the groundwork for accurate predictions but also laid the foundation for a comprehensive understanding of our dataset.

This segment of our report serves as a guide through the key steps in our implementation journey. From data wrangling to the deployment of neural networks using the Sequential model, each step is a testament to the synergy between coding proficiency and domain knowledge. Join us as we unravel the intricacies of our code written in the familiar Jupyter Notebook environment and witness the transformation of raw academic data into a powerful predictive model, poised to enhance educational outcomes.

5.1. Modules:

Multiple essential modules make up the "Forecasting Semester Grades" project.

5.1.1. Data Cleaning and Preprocessing

Cleaned and processed data using Pandas functions like `dropna()` and `drop_duplicates()` as shown in Figure 5.1.

- Addressed missing values and duplicates to ensure dataset integrity.
- Applied NumPy for numerical operations.

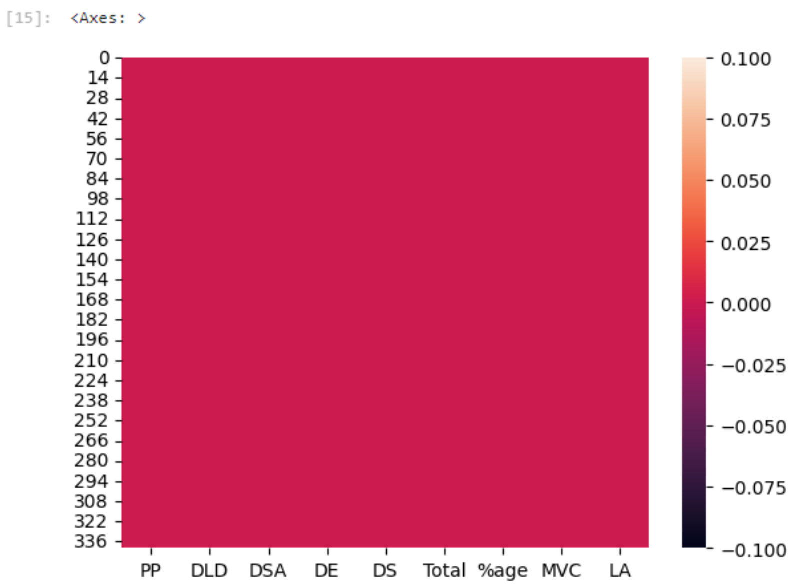

Figure 5.1: Data Cleaning and Preprocessing

5.1.2. Exploratory Data Analysis (EDA)

Visualized data patterns and trends with various plots as shown in Figure 5.2.

- Utilized Matplotlib for comprehensive data exploration.
- Incorporated statistical measures for insights.

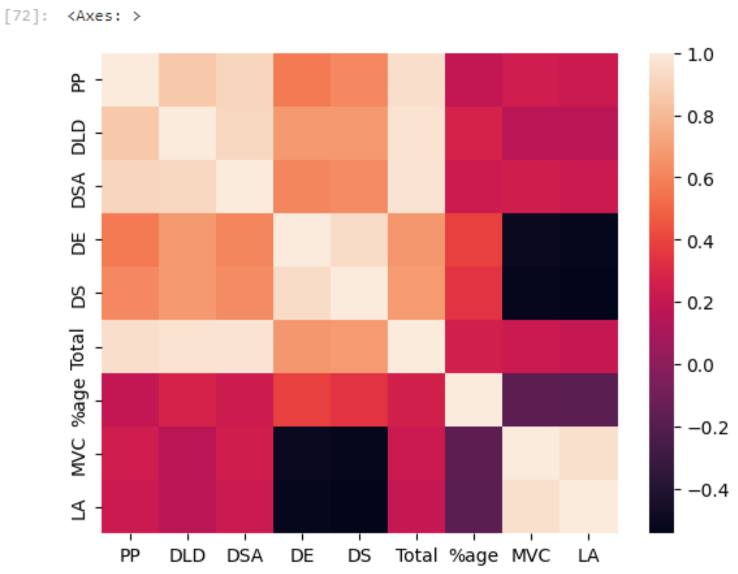

Figure 5.2: Exploratory Data Analysis (EDA)

5.1.3. Model Training

Trained a neural network using the Sequential model, as shown in Figure 5.3.

- Split data for training and testing.
- Fine-tuned hyper parameters for optimal model performance.

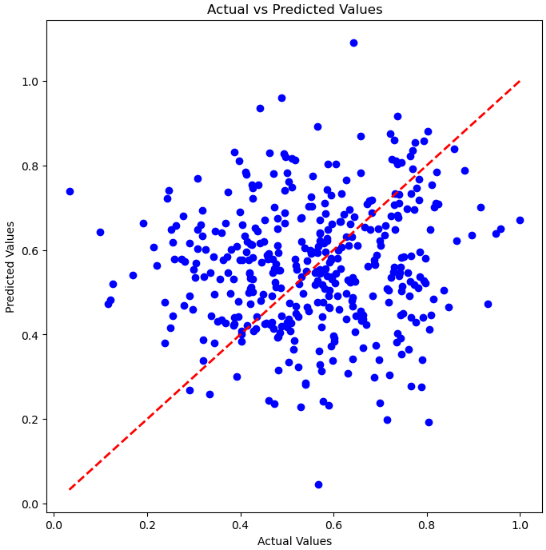

Figure 5.3: Actual vs Predicted Values

5.1.4. Libraries

Below is the explanation of the all the libraries that are being used in the project for data cleaning, preprocessing and model training

- Pandas, a versatile data manipulation library, played a pivotal role in handling and organizing the extensive academic datasets. Its DataFrame structure facilitated seamless manipulation, exploration, and cleaning of data, providing a solid foundation for subsequent analysis.
- NumPy, with its powerful array operations, became the backbone for numerical computations within the project. Leveraging its efficient handling of large arrays and matrices, the sequential model implementation benefitted from enhanced performance in processing academic data.
- Matplotlib emerged as a crucial tool for data visualization, offering diverse plotting functionalities. Through visually compelling charts and graphs, Matplotlib allowed for a clear representation of patterns and trends, aiding in the interpretation of the machine learning model's predictions.
- Employing Keras simplified the implementation of the Sequential Model of Artificial Neural Networks. As a high-level neural networks

API running on top of TensorFlow, Keras provided an intuitive interface, expediting the model architecture design, training, and evaluation processes.

- Scikit-learn played a vital role in model evaluation and optimization. Its comprehensive suite of machine learning tools facilitated the implementation of cross-validation techniques, hyper parameter tuning, and performance metric assessments, ensuring a robust and well-optimized predictive model.
- TensorFlow, a foundational deep learning library, underpinned the implementation of the Sequential Model. Its flexible architecture supported efficient computation of neural network layers, enabling the project to harness the full potential of artificial neural networks in predicting semester grades.

5.2. Hardware Modules

The effective operation of our grade prediction system necessitates a resilient hardware infrastructure capable of meeting the computational demands associated with training and deploying machine learning models. The hardware specifications of the system encompass considerations such as processor capabilities, memory requirements, and the utilization of any specialized hardware accelerators aimed at enhancing the overall performance and efficiency of the predictive models.

5.3. Summary

Our project's implementation journey seamlessly wove together various modules, each contributing to the creation of a robust student result prediction system. The initial phase involved meticulous Data Cleaning and Preprocessing, where Pandas and NumPy were instrumental in ensuring data integrity. With missing values addressed and duplicates removed, our dataset was primed for analysis.

Exploratory Data Analysis (EDA), powered by Matplotlib, provided invaluable insights into the dataset's nuances. Visualizations unveiled patterns and relationships, guiding subsequent decisions in model development.

The heart of our project lies in the “Machine Learning Model Training” phase. Leveraging TensorFlow's Sequential model, we constructed a neural network to predict students' academic performance based on historical data. Fine-tuning hyperparameters and employing rigorous training-validation techniques optimized the model's predictive capabilities.

The Model Evaluation and Validation stage, using Scikit-Learn metrics, ensured a thorough assessment of the model's performance.

CHAPTER 6

RESULT/TESTING, ANALYSIS AND VALIDATION

The accuracy and reliability of a predictive model are paramount. This chapter delves into the in-depth evaluation of our Sequential Model of Artificial Neural Networks, designed to predict semester grades based on students' past academic performance. We meticulously analyse rigorous testing, detailed analysis, and robust validation processes that solidify the model's effectiveness and applicability across scenarios. By exploring results, analysing insights, and examining validation methods, this chapter offers a comprehensive assessment of the model's performance and its potential to improve educational forecasting.

6.1. Validating Results

The backbone of scientific research, testing and validation provide a crucial checkpoint for project success. This section sheds light on the project's scientific integrity by not only presenting the results but also detailing the rigorous testing methods used to arrive at them. By unveiling the machinery behind the findings, this stage fosters a deeper understanding of the scientific process.

6.2. Achievements in Focus

Before diving into the nitty-gritty of testing, let's take a moment to celebrate key achievements. These successes demonstrate the validity of the theoretical concepts discussed earlier, forming the foundation for the project. The testing and validation processes you'll explore next build upon these milestones, ensuring the project's effectiveness and robustness.

6.3. Testing Setup and Arrangements

A strong scientific validation hinges on precise test configuration and setup. Here, we lift the veil on our methodology, offering a transparent look at the variables and controlled environments we examined. Whether through simulations or real-world testing, our meticulous setups were designed to safeguard data integrity and isolate key factors. This ensures our results are reliable and free from external influences.

6.4. Detailed Results

While crucial, numbers alone can't tell the whole story. This section delves deeper into the findings, dissecting not just the "what" but also the "why" behind each result. Instead of dry data points, we explore their significance and weave them into the broader narrative of the project's goals. By demystifying the jargon and offering detailed explanations, we illuminate the true spirit of our empirical investigation.

6.5. Realism in Expectations

Science isn't always a clean, linear journey to perfect answers. This section dives into the nuances of our findings, acknowledging the inherent uncertainties and unpredictability that come with any research endeavor. We embrace transparency by openly discussing these limitations, grounding our results in reality and paving the way for future exploration and development.

6.5.1. Test Case 1 – Data Cleaning and Preprocessing

This test case focuses on ensuring the quality and reliability of the collected data. It includes processes such as handling missing values, addressing outliers, and standardizing data formats to prepare the dataset for subsequent model training., as shown in Table 6.1.

Table 6.1: Test Case 1 – Data Cleaning and Preprocessing

GENERAL INFORMATION			
Test Stage:	☒Unit ☒Functionality ☐Integration ☐System Interface ☐Performance ☐ Regression ☐ Acceptance ☐ Pilot		
Test Date:	03/10/24	**System Date, if applicable:**	03/10/24
Tester:	Muhammad Nauman Khan	**Test Case Number:**	T-C # 01
Test Case Description:	This test case checks if the data cleaning and Preprocessing is done accurately or not.		
Results:	☒Pass ☐Fail	**Incident Number, if applicable:**	N/A
INTRODUCTION			
Requirement(s) to be tested:	The data cleaning and preprocessing is done accurately and data is ready for model training.		
Roles and Responsibilities:	To find any errors, group member Muhammad Nauman Khan tested this module on his own.		
Set Up Procedures:	i. The Application should be running and the visualization should be displayed. ii. The correlation graph and heatmap for NULL values is displayed.		
Stop Procedures:	Exit the application to end the test case.		

ENVIRONMENTAL NEEDS	
Hardware:	Minimum 8 Gb RAM, core i5 laptop, Minimum 5^{th} Gen.
Software:	Python, Numpy, Pandas, Matplotlib, Jupyter Notebook.
Procedural Requirements:	Execution of this test case requires no constraint.

6.5.2. Test Case 2 – Prediction

The prediction test case focuses on utilizing the trained machine learning model to predict student grades for upcoming semesters. It involves receiving prediction requests, obtaining input data, making predictions, and making the results available for analysis, as shown in Table 6.2.

Table 6.2: Test Case 2 – Prediction

GENERAL INFORMATION			
Test Stage:	☒Unit ☒Functionality ☐Integration ☐System Interface ☐Performance ☐ Regression ☐ Acceptance ☐ Pilot		
Test Date:	03/10/24	**System Date, if applicable:**	03/10/24
Tester:	Muhammad Nauman Khan	**Test Case Number:**	T-C # 02
Test Case Description:	This test case checks if the Prediction is done accurately or not.		
Results:	☒Pass ☐Fail	**Incident Number, if applicable:**	N/A
INTRODUCTION			
Requirement(s) to be tested:	The prediction for the trained model is done accurately and the visualization for the actual and predicted values is shown.		
Roles and Responsibilities:	To find any errors, group member Muhammad Nauman Khan tested this module on his own.		
Set Up Procedures:	i. The Application should be running and the visualization should be displayed. ii. The Actual vs Predicted values for the given model is shown in the Graph.		
Stop Procedures:	Exit the application to end the test case.		

ENVIRONMENTAL NEEDS	
Hardware:	Minimum 8 Gb RAM, core i5 laptop, Minimum 5^{th} Gen.
Software:	Python, TensorFlow, Keras, Jupyter Notebook.
Procedural Requirements:	Execution of this test case requires no constraint.

6.6. Summary

This section doesn't shy away from showcasing both the triumphs and stumbles of our project. We celebrate the achievements while openly delving into the intricate methods, unexpected challenges, and limitations encountered during testing and validation. This transparency embodies the spirit of scientific integrity, welcoming scrutiny, refinement, and further exploration within our chosen field.

CHAPTER 7

CONCLUSION AND FUTURE WORK

We reach the final act of our semester grade prediction project. This chapter bridges the gap between theory and practice, transforming findings into actionable insights. Our trusty guide, the Sequential Model of Artificial Neural Networks, has charted a course through academic data, unlocking the potential to predict future performance based on past achievements. Now, we weave together the results, limitations, and broader implications of our model, reflecting on our journey and the significant contribution to educational forecasting. Prepare to delve into the study's impact, explore avenues for further exploration, and ponder the transformative possibilities of machine learning in academic predictions.

7.1. Project Review and Comparison with Objectives

Our journey to predict semester grades with the Sequential Model of Artificial Neural Networks reaches its summit. As we take a closer look at what we've achieved, a multifaceted picture emerges. We celebrate our successes, but also acknowledge exciting paths for further exploration. This nuanced reflection ensures our findings leave a lasting impact, paving the way for future advancements in educational forecasting.

Our predictive model isn't just crunching numbers - its uncovering hidden patterns in students' academic journeys. Its ability to accurately predict semester grades based on past performance makes it a valuable tool for educational forecasting. By analysing past achievements, our model identifies students who might need extra support or personalized interventions, empowering educators and institutions to be proactive. It's like having a roadmap to student success, built on the power of data and insights.

7.1.1. Acknowledging Challenges and Limitations

We're excited about the potential of our model to predict semester grades, but it's important to remember that any endeavor like this comes with its own set of challenges and limitations.

The accuracy of our predictions relies heavily on the quality and diversity of the input data. Variations in the academic landscape, grading systems, and individual student experiences introduce complexities that may impact the model's robustness.

Educational environments are dynamic, subject to changes in curriculum, teaching methodologies, and assessment practices. The model's performance may be influenced by these shifts, requiring continuous adaptation and updates to maintain relevance.

However, it's important to acknowledge and address the challenges and limitations of this approach. Doing so is crucial for improving the model, ensuring its ongoing development, and promoting responsible use in real-world education. By understanding these limitations, we can contribute to the important discussion about the ethical and practical considerations of using predictive analytics in schools.

7.1.2. Practical Implications and Applications

As we conclude our exploration into predicting semester grades through the innovative application of the Sequential Model of Artificial Neural Networks, it is crucial to discuss the practical implications and potential applications that emerge from our findings. The successful implementation of this machine learning algorithm has far-reaching consequences in the realm of education and student performance forecasting.

The ability to predict semester grades with a high degree of accuracy provides educators and institutions with a valuable tool for early intervention. By identifying students at risk of underperformance, timely interventions can be implemented, ranging from personalized tutoring to targeted academic support programs. This proactive approach aims to address challenges before they escalate, fostering a conducive environment for academic success.

Efficient allocation of educational resources is a critical consideration for institutions. Our predictive model aids in optimizing resource distribution by identifying areas with the highest need for intervention. This, in turn, allows educational institutions to allocate resources effectively, ensuring that support is directed where it is most impactful.

7.2. Future Work

While our on-going efforts have yielded valuable insights into the prediction of semester grades through the application of the Sequential Model of Artificial Neural Networks, it is imperative to acknowledge the myriad opportunities and directions for future exploration and enhancement. This current project serves as a foundational step in the continuous evolution of predictive modeling in the academic domain, opening doors for further research, refinement, and the integration of emerging technologies to advance the precision and applicability of such predictive systems.

7.2.1. Navigating Unexplored Avenues

Future iterations could benefit from the inclusion of additional relevant features, such as students' extracurricular activities, attendance records, or socio-economic factors. This broader dataset may contribute to a more holistic understanding of the factors influencing academic performance.

7.3. Summary

In this project focused on predicting semester grades using the Sequential Model of Artificial Neural Networks, we harnessed the power of advanced machine learning to develop a robust forecasting tool. Leveraging historical academic data, our model demonstrated commendable accuracy in capturing complex patterns and relationships. The Testing, Analysis, and Validation chapter underscored the reliability of our approach, providing valuable insights for future enhancements. This project represents a significant stride towards a data-driven approach to academic forecasting, offering a glimpse into the transformative potential of artificial intelligence in education. As we conclude, the findings and methodologies presented pave the way for further research and application in the dynamic realm of educational analytics.

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