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**S. P. Mandali's**

**RAMNARAIN RUIA AUTONOMOUS COLLEGE**

**MATUNGA, MUMBAI – 400019**

**DEPARTMENT OF COMPUTER SCIENCE & IT**

**FIELD PROJECT REPORT**

**Course Code: RPSCSP.0605**

**Study on Student’s Habits and Routine**

**Guide Name**

**Rasika Mundhe**

**Submitted By**

**Shantanu Harkulkar**

**Seat No - 166**

**M. Sc Sem II Computer Science**

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## 

## A] Problem Definition

Student academic performance is influenced by various factors including study habits, procrastination patterns, mental wellbeing, and demographic variables. However, traditional methods of analysing these factors often rely on manual interpretation of survey data, which can be time-consuming and less insightful.

The **Student’s Habits and Routine on Academic Performance Analyzer** project aims to address this gap by developing a data-driven approach to analyse student survey data. By leveraging data science techniques, the project seeks to uncover meaningful insights into student performance, identify key patterns in study behaviours, and establish correlations between various factors affecting academic outcomes.

This approach will enable educational institutions to design more effective interventions, provide targeted support, and create environments conducive to improved student performance and wellbeing.

## B] Introduction

### Motivation

Student performance plays a crucial role in academic success and future career prospects. Understanding the underlying factors that influence performance is essential for developing effective educational strategies and support systems. Traditional methods of assessment often fail to capture the complex interplay of variables affecting student outcomes. This project is motivated by the need to leverage data science techniques to gain deeper insights into student behaviours, procrastination patterns, and wellbeing factors that impact academic performance.

### Problem Statement

The problem lies in the lack of comprehensive understanding and systematic approach to analysing the multifaceted factors influencing student performance. Educational institutions need data-driven insights to develop targeted interventions that address specific challenges faced by students. There is a need to identify correlations between study habits, procrastination tendencies, mental wellbeing, and academic outcomes.

### Purpose/Objective and Goals

The purpose of this project is to analyse and evaluate various factors affecting student performance through survey data. The primary objectives include:

* Analysing demographic data and study habits to identify patterns and trends
* Identifying procrastination behaviours and their impact on academic outcomes
* Performing sentiment analysis on text-based survey responses to understand student perspectives
* Generating actionable insights for improving student wellbeing and academic performance
* Developing a framework for ongoing assessment and intervention

### Literature Survey

Existing literature highlights the significance of various factors in determining student performance. Research by Smith et al. (2019) indicates that sleep patterns significantly impact cognitive function and learning capacity. Johnson's (2020) study demonstrates that effective time management strategies correlate with improved academic outcomes. Furthermore, Zhang and Lee (2021) found strong associations between mental health indicators and academic performance.

Despite these insights, there is a lack of comprehensive studies that integrate multiple factors using data science techniques to provide actionable recommendations for educational institutions. This project aims to address this gap by applying advanced analytical methods to survey data.

### Project Scope and Limitations

### Scope:

* Analysing survey data collected from students to identify factors affecting performance
* Applying sentiment analysis to text-based responses
* Identifying correlations between different variables
* Developing visualizations to communicate insights effectively
* Providing recommendations based on data analysis

### Limitations:

* Insights depend on the quality and quantity of survey responses
* Self-reported data may contain inherent biases
* Analysis is limited to factors included in the survey
* Real-time monitoring capabilities are not included in the current scope
* The project does not implement interventions but provides recommendations

## C] Case Study

### Existing Systems

Traditional approaches to understanding student performance rely heavily on grade analysis, periodic assessments, and occasional surveys. These methods often involve manual interpretation and basic statistical analysis, which are time-consuming and may miss complex patterns. Existing systems typically:

* Focus primarily on academic outcomes rather than underlying factors
* Utilize basic statistical methods without leveraging advanced data science techniques
* Analyse different factors in isolation rather than exploring correlations
* Lack systematic approaches to sentiment analysis of qualitative responses

### Detailed Explanation of Study Area

The study focuses on understanding student performance based on various factors, including:

* **Demographics**: Age, gender, program of study, year level
* **Study Habits**: Hours spent studying, preferred study environments, resource utilization
* **Procrastination Patterns**: Frequency, triggers, impact on deadlines
* **Mental Wellbeing**: Stress levels, sleep patterns, work-life balance
* **Text-based Responses**: Qualitative insights into challenges and success factors

### Scope and Limitations of Existing Systems

While traditional methods provide some insights into student performance, they have significant limitations:

* Limited ability to process large volumes of survey data efficiently
* Difficulty in identifying complex correlations between multiple factors
* Lack of advanced text analysis capabilities for qualitative responses
* Insufficient visualization tools for communicating insights effectively
* Absence of data-driven recommendations for interventions

### Project Perspective and Features

The Student Performance Analyzer offers a comprehensive solution that addresses the limitations of existing systems:

* **Data-driven Decision Making**: Leveraging advanced analytics for evidence-based interventions
* **Comprehensive Factor Analysis**: Examining correlations between multiple variables
* **Text Analysis**: Applying sentiment analysis to extract insights from qualitative responses
* **Interactive Visualizations**: Creating intuitive representations of complex data patterns
* **Actionable Recommendations**: Providing specific suggestions based on analytical findings

### Stakeholders

The project involves several key stakeholders:

* **Educational Institutions**: Universities and colleges seeking to improve student outcomes
* **Students**: Beneficiaries of improved support systems and interventions
* **Faculty and Academic Advisors**: Those responsible for implementing recommendations
* **Educational Researchers**: Professionals interested in academic performance factors
* **Administrative Staff**: Personnel involved in student support services

### Data Collection Methods with Proof

Data collection was conducted through a structured survey using Google Forms. The survey included:

* Demographic questions
* Likert scale items for measuring study habits and procrastination
* Multiple-choice questions about wellbeing factors
* Open-ended questions for qualitative insights

Below is the link of Circulated form which includes questionnaire for data collection:

<https://docs.google.com/forms/d/e/1FAIpQLSfU1QLIZDCRmkWB9sfQaSibkgrRwrWyLkozJEYc-Twh-h9wFA/viewform?usp=header>

### Requirement Analysis

**Functional Requirements:**

* Data uploading and preprocessing capabilities
* Text analysis for sentiment extraction
* Statistical analysis for correlation identification
* Visualization tools for insight communication
* Reporting features for summarizing findings

**Performance Requirements:**

* Efficient processing of survey datasets
* Responsive visualization rendering
* Scalable computation for larger datasets

**Security Requirements:**

* Data anonymization to protect student privacy
* Secure storage of survey responses
* Compliance with data protection regulations
* Access controls for sensitive information

## D] Research Methodology

### Objective

The primary objective of this research is to identify key factors affecting student performance and provide data-driven insights for developing effective interventions to improve academic outcomes and student wellbeing.

### Hypothesis

There is a significant correlation between procrastination patterns, wellbeing factors, study habits, and academic performance among students. Furthermore, sentiment analysis of qualitative responses can reveal underlying issues not captured by quantitative measures.

### Scope of Study

The study encompasses the analysis of survey data collected from undergraduate and graduate students, focusing on multiple dimensions of student behaviour and experience. It includes both quantitative analysis of structured responses and qualitative analysis of text-based feedback.

### Limitations

* **Sample Representation**: The study is limited to students who completed the survey
* **Self-reported Data**: Results depend on the accuracy of self-reporting
* **Temporal Constraints**: The study represents a snapshot in time rather than longitudinal data
* **Limited Variables**: Only factors included in the survey can be analysed

### Significance of Research

This research addresses a critical need in educational settings by providing evidence-based insights into student performance factors. The findings will enable institutions to:

* Develop targeted interventions for at-risk students
* Create more effective support systems
* Allocate resources more efficiently
* Design better educational environments
* Improve overall student outcomes and satisfaction

### Sample Size

The target sample size for this study is 100-200 student responses, representing diverse academic programs, year levels, and demographic backgrounds. This sample size provides sufficient statistical power while remaining manageable for detailed analysis.

### Sources of Data Collection

Primary data was collected through a comprehensive Google Forms survey distributed to students through official channels. The survey was designed to capture information on:

* Demographic details
* Study habits and preferences
* Procrastination tendencies
* Wellbeing indicators
* Open-ended reflections on academic experiences

### Model Selection and Validation

The project employs multiple analytical models selected for their appropriateness to different aspects of the data:

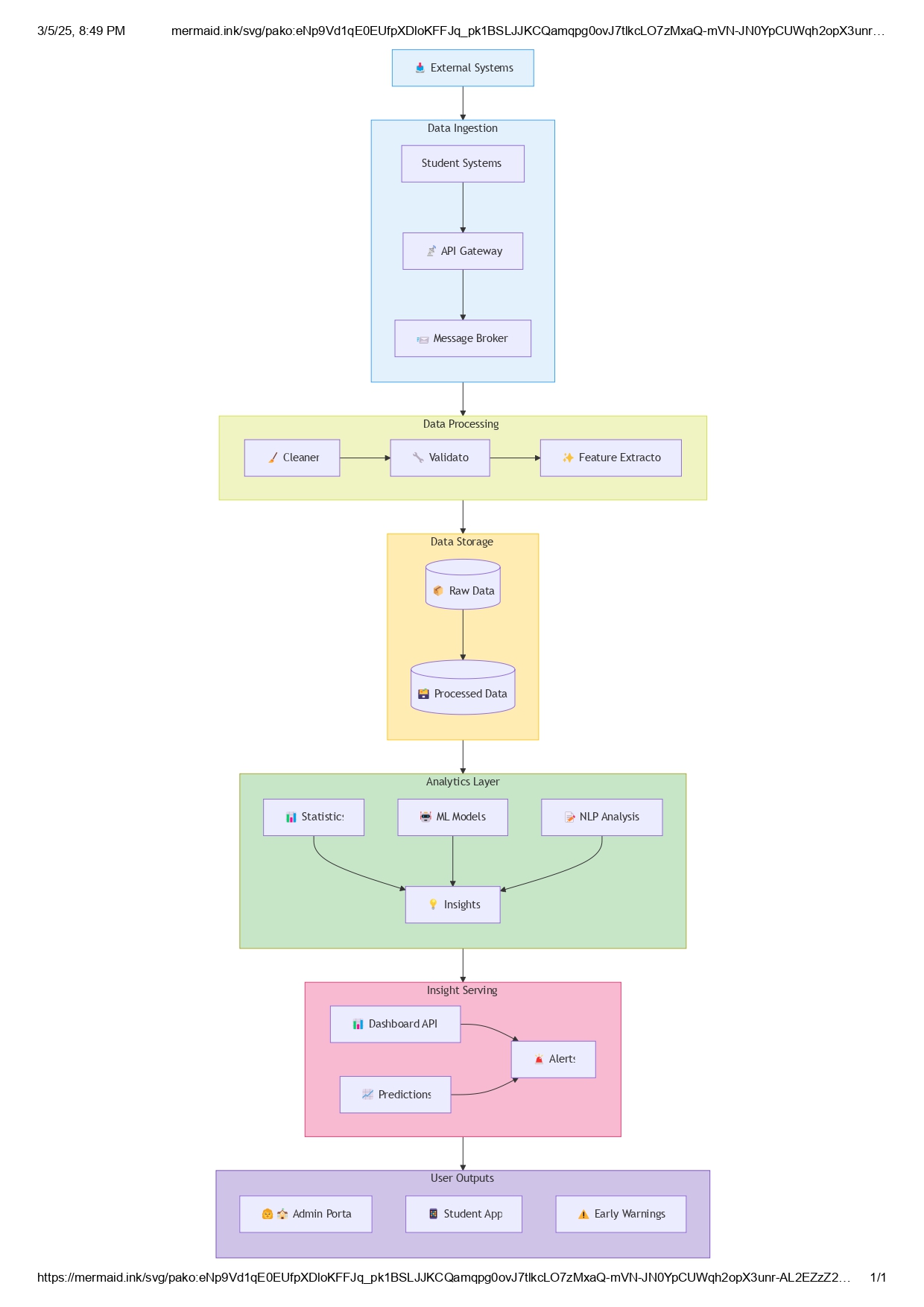
* **K-Means Clustering**: Used to identify patterns in student behaviours and group similar response profiles
* **Sentiment Analysis Models**: Applied to text responses to extract emotional content and themes
* **Correlation Analysis**: Used to identify relationships between different variables
* **Statistical Tests**: Applied to validate findings and test hypotheses

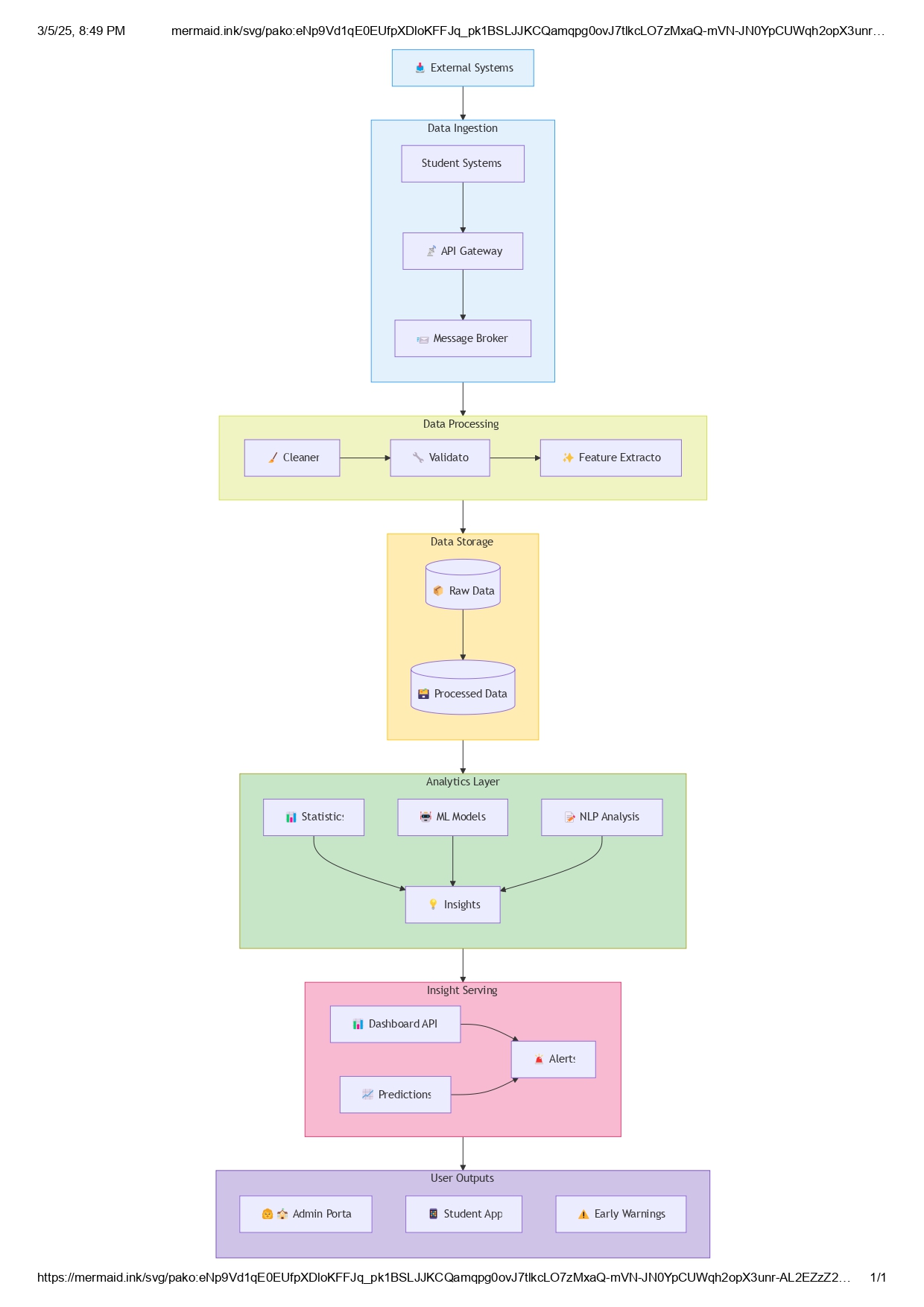
### Model validation was performed using:

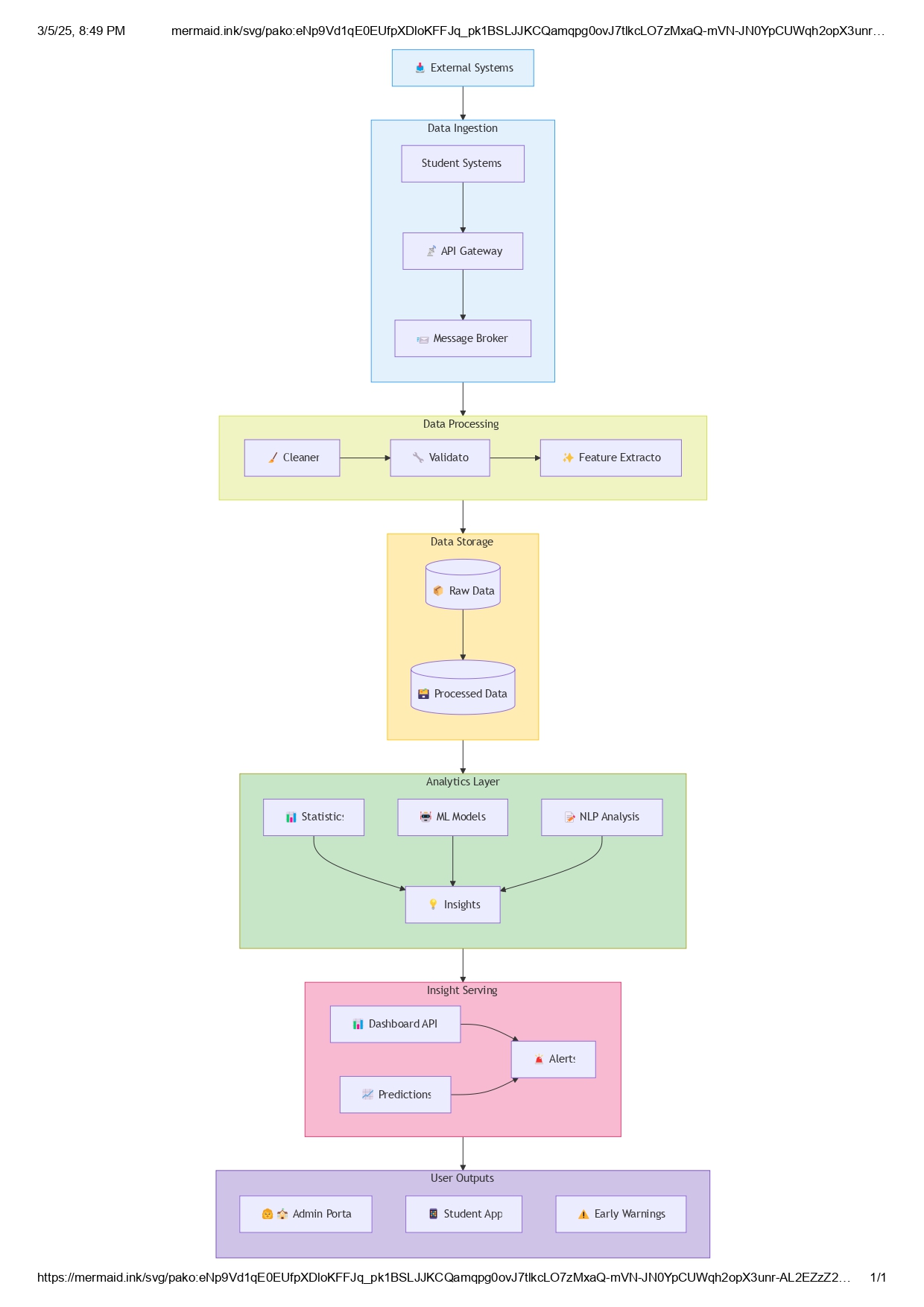
* Cross-validation techniques
* Split testing (training/testing data sets)
* Comparison with baseline models
* Domain expert review of findings

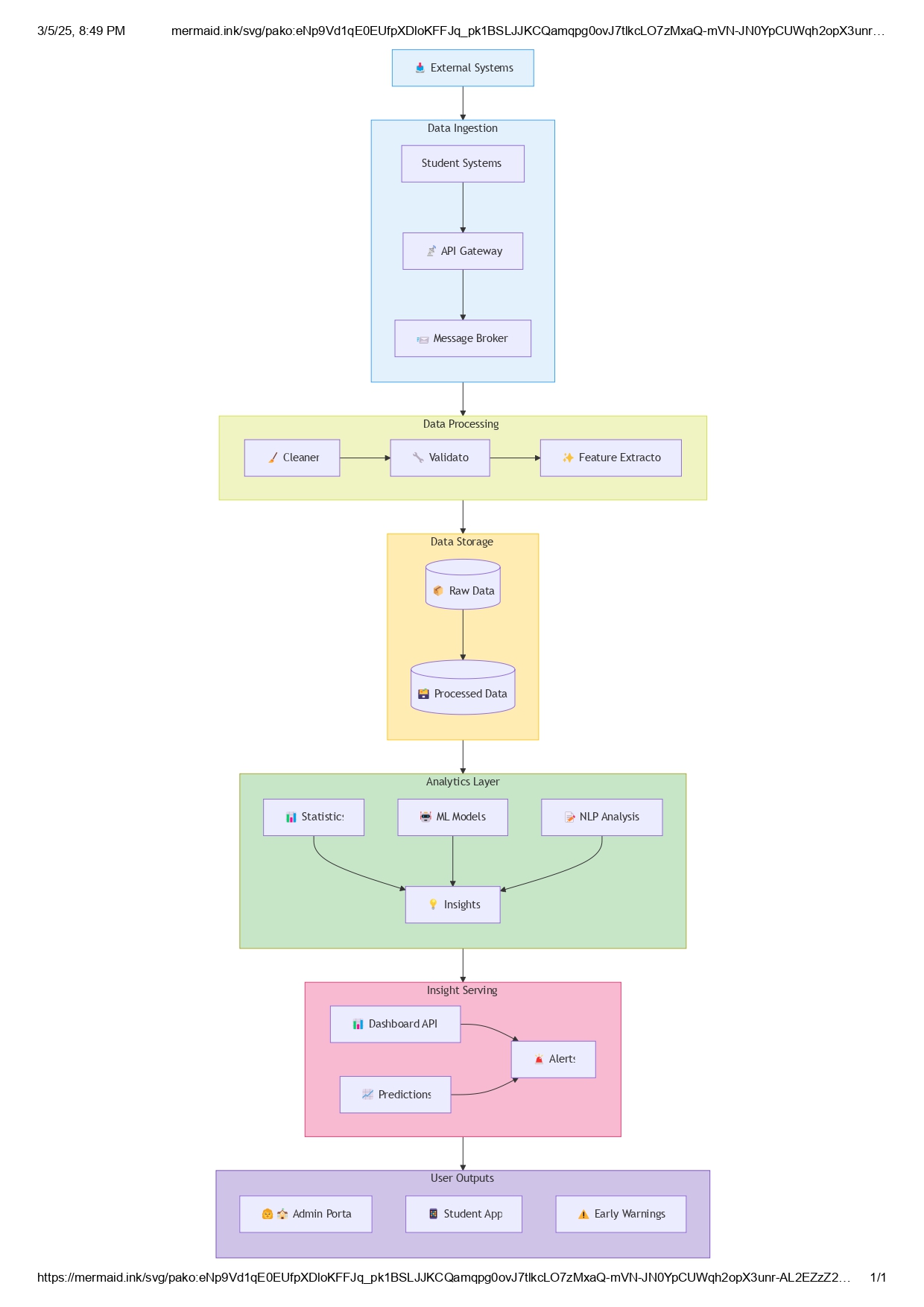
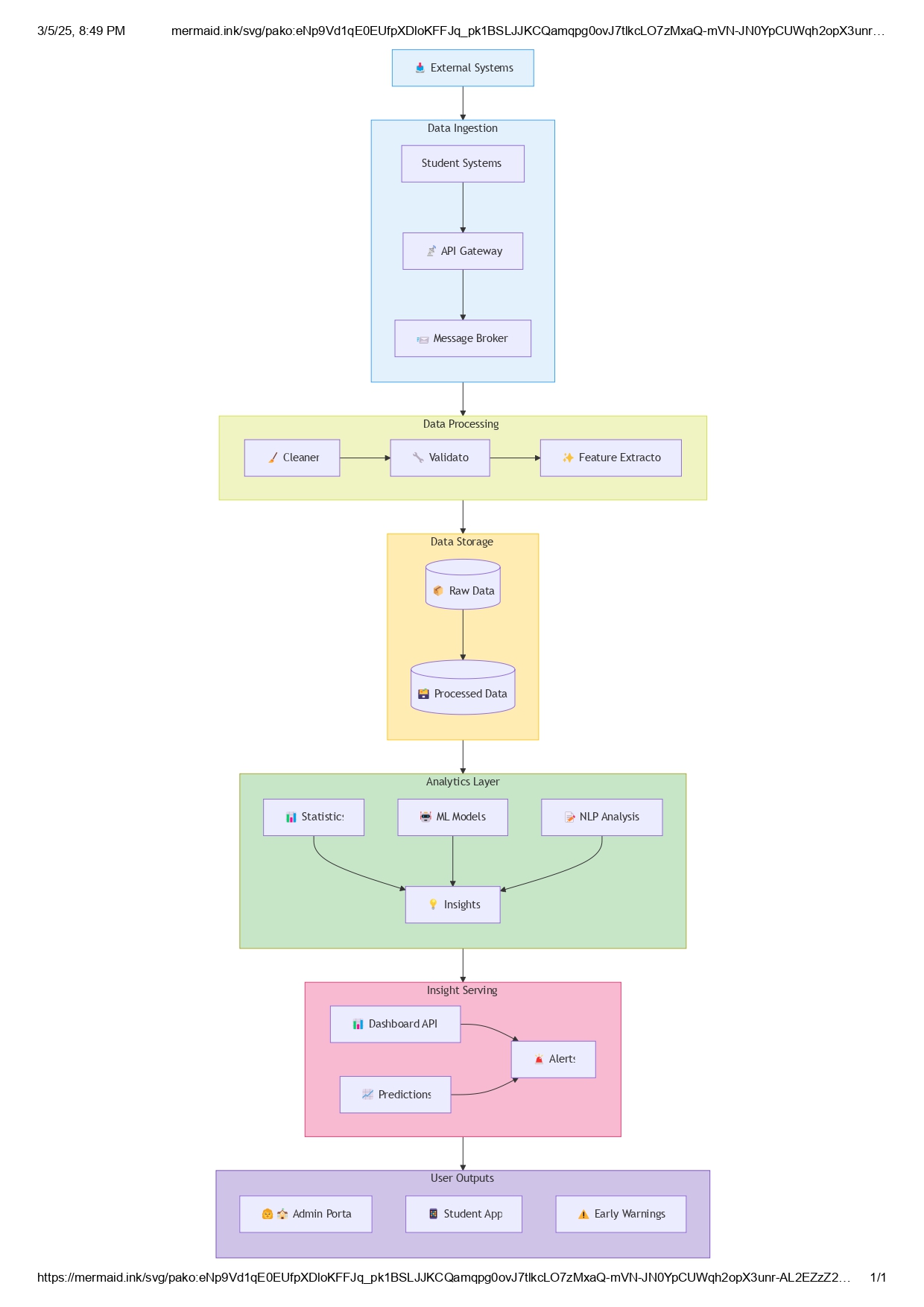
### Model Explanation

* **K-Means Clustering**: An unsupervised machine learning algorithm that groups data points based on similarity, helping identify distinct patterns in student responses
* **Sentiment Analysis**: Natural Language Processing techniques that classify text responses according to emotional tone (positive, negative, neutral)
* **Correlation Analysis**: Statistical methods to measure the strength and direction of relationships between different variables
* **Descriptive Statistics**: Basic statistical measures to summarize and interpret survey responses
* **Data Flow Diagram:**

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### Summary Explanation

The data flow diagram (DFD) illustrates how information moves through the Student Performance Analyzer system:

**Key Components**

1. **External Entities** (blue rectangles):
   * Students: Primary data providers who complete surveys
   * Educational Institutions: End users who receive analysis results
   * Researchers: Secondary stakeholders who utilize research findings
2. **Core Processes** (green circles):
   * Process 1.0 (Data Collection): Gathers survey responses from students
   * Process 2.0 (Data Preprocessing): Cleans and prepares raw data
   * Process 3.0 (Statistical Analysis): Performs statistical computations
   * Process 4.0 (ML & NLP Analysis): Applies machine learning and natural language processing
   * Process 5.0 (Visualization): Creates visual representations of analysis results
   * Process 6.0 (Insight Generation): Synthesizes findings into actionable recommendations
3. **Data Stores** (yellow rectangles):
   * D1 (Survey Data): Repository for raw collected survey responses
   * D2 (Processed Data): Storage for cleaned and transformed data

### Data Flow Paths

* Student survey responses enter the system through the Data Collection process
* Raw data is stored temporarily before preprocessing
* Processed data branches into two analysis paths: statistical and ML/NLP
* Analysis results flow into visualization and insight generation
* Final insights are delivered to both educational institutions and students

The diagram effectively captures the complete lifecycle of data in the system, from initial collection through processing, analysis, and final delivery of actionable insights to stakeholders

## E] Experimental Setup

### Tools

The implementation of the models involved the use of the following tools:

* **Python**: Utilized as the primary programming language for data preprocessing, model development, and analysis
* **Pandas & NumPy**: Employed for data manipulation and numerical operations
* **Scikit-learn**: Used for implementing machine learning algorithms such as K-means clustering and correlation analysis
* **NLTK & Transformers**: Applied for natural language processing and sentiment analysis
* **Matplotlib & Plotly**: Utilized for data visualization and creating interactive charts
* **Stream lit**: Employed for developing the web-based interface
* **Jupyter Notebook**: Used for exploratory data analysis and prototyping

### Architecture/Framework

The project follows a modular architecture consisting of several interconnected components:

### 

1. **Data Collection Module**: Handles survey data import and preprocessing
2. **Analysis Engine**: Contains algorithms for statistical analysis, clustering, and sentiment analysis
3. **Visualization Component**: Generates charts, graphs, and interactive displays
4. **Reporting System**: Compiles insights and recommendations into structured reports
5. **Web Interface**: Provides user access through a Stream lit-based application

This architecture enables efficient data processing, analysis, and presentation while maintaining flexibility for future enhancements.

### Software Language

Python was selected as the primary programming language due to its:

* Rich ecosystem of data science libraries
* Strong capabilities for statistical analysis
* Excellent support for machine learning implementation
* Robust tools for natural language processing
* Flexible visualization options
* Compatibility with web application frameworks

The project leverages Python 3.8+ to ensure access to the latest features and libraries.

### Testing

Testing was conducted at multiple levels to ensure the reliability and accuracy of the system:

* **Unit Testing**: Individual components were tested in isolation
* **Integration Testing**: Interactions between modules were verified
* **Validation Testing**: Results were compared with manual analysis on sample data
* **User Acceptance Testing**: The interface and reports were evaluated by education professionals

Performance testing was also conducted to ensure efficient processing of larger datasets.

## F] Data Analysis & Interpretation

### Screen Layout

The Student Performance Analyzer features a streamlined, user-friendly interface with several key screens:

**1. Data Upload & Overview Dashboard**

* Allows uploading of survey data files
* Displays summary statistics and key metrics
* Provides navigation to detailed analysis sections

**2. Demographic & Study Habits Analysis**

* Visualizes student demographic distributions
* Presents study habit patterns across different groups
* Shows correlations between demographics and study preferences

**3. Procrastination Analysis Dashboard**

* Identifies common procrastination patterns
* Visualizes procrastination intensity across student groups
* Maps relationships between procrastination and performance

**4. Wellbeing Factors Dashboard**

* Analyses stress levels, sleep patterns, and work-life balance
* Shows correlations between wellbeing indicators and academic performance
* Highlights at-risk groups based on wellbeing metrics

**5. Text Analysis & Sentiment Dashboard**

* Presents results of sentiment analysis on open-ended responses
* Identifies common themes and keywords
* Visualizes sentiment distribution across different student segments

**6. Recommendations & Insights**

* Summarizes key findings from all analysis components
* Provides actionable recommendations based on data insights
* Offers downloadable reports for stakeholders

Each screen includes interactive elements allowing users to filter data, adjust visualizations, and explore different aspects of the analysis.

### Coding

Key components of the implementation include:

**Data Preprocessing**

import pandas as pd

import numpy as np

def preprocess\_survey\_data(df):

# Handle missing values

df = df.fillna({

'study\_hours': df['study\_hours'].median(),

'procrastination\_level': df['procrastination\_level'].median()

})

# Create derived features

df['wellbeing\_score'] = (df['sleep\_quality'] + df['stress\_level'] + df['work\_life\_balance']) / 3

# Encode categorical variables

df = pd.get\_dummies(df, columns=['preferred\_study\_environment', 'program'])

return df

### Sentiment Analysis Implementation

from nltk.sentiment.vader import SentimentIntensityAnalyzer

import nltk

nltk.download('vader\_lexicon')

def analyze\_sentiment(text):

sia = SentimentIntensityAnalyzer()

sentiment\_score = sia.polarity\_scores(text)

if sentiment\_score['compound'] >= 0.05:

return 'Positive'

elif sentiment\_score['compound'] <= -0.05:

return 'Negative'

else:

return 'Neutral'

# Apply sentiment analysis to open-ended responses

df['sentiment'] = df['challenges\_response'].apply(analyze\_sentiment)

### Clustering Implementation

from sklearn.cluster import KMeans

from sklearn.preprocessing import StandardScaler

def cluster\_students(df, features, n\_clusters=3):

# Select and scale features

X = df[features]

scaler = StandardScaler()

X\_scaled = scaler.fit\_transform(X)

# Apply K-means clustering

kmeans = KMeans(n\_clusters=n\_clusters, random\_state=42)

df['cluster'] = kmeans.fit\_predict(X\_scaled)

return df, kmeans.cluster\_centers\_

### Visualization Example

import plotly.express as px

def create\_procrastination\_heatmap(df):

# Create correlation matrix

corr\_matrix = df[['procrastination\_level', 'study\_hours',

'assignment\_completion', 'grade\_average']].corr()

# Generate heatmap

fig = px.imshow(corr\_matrix,

text\_auto=True,

color\_continuous\_scale='Blues')

fig.update\_layout(

title="Correlation between Procrastination and Performance",

xaxis\_title="Factors",

yaxis\_title="Factors"

)

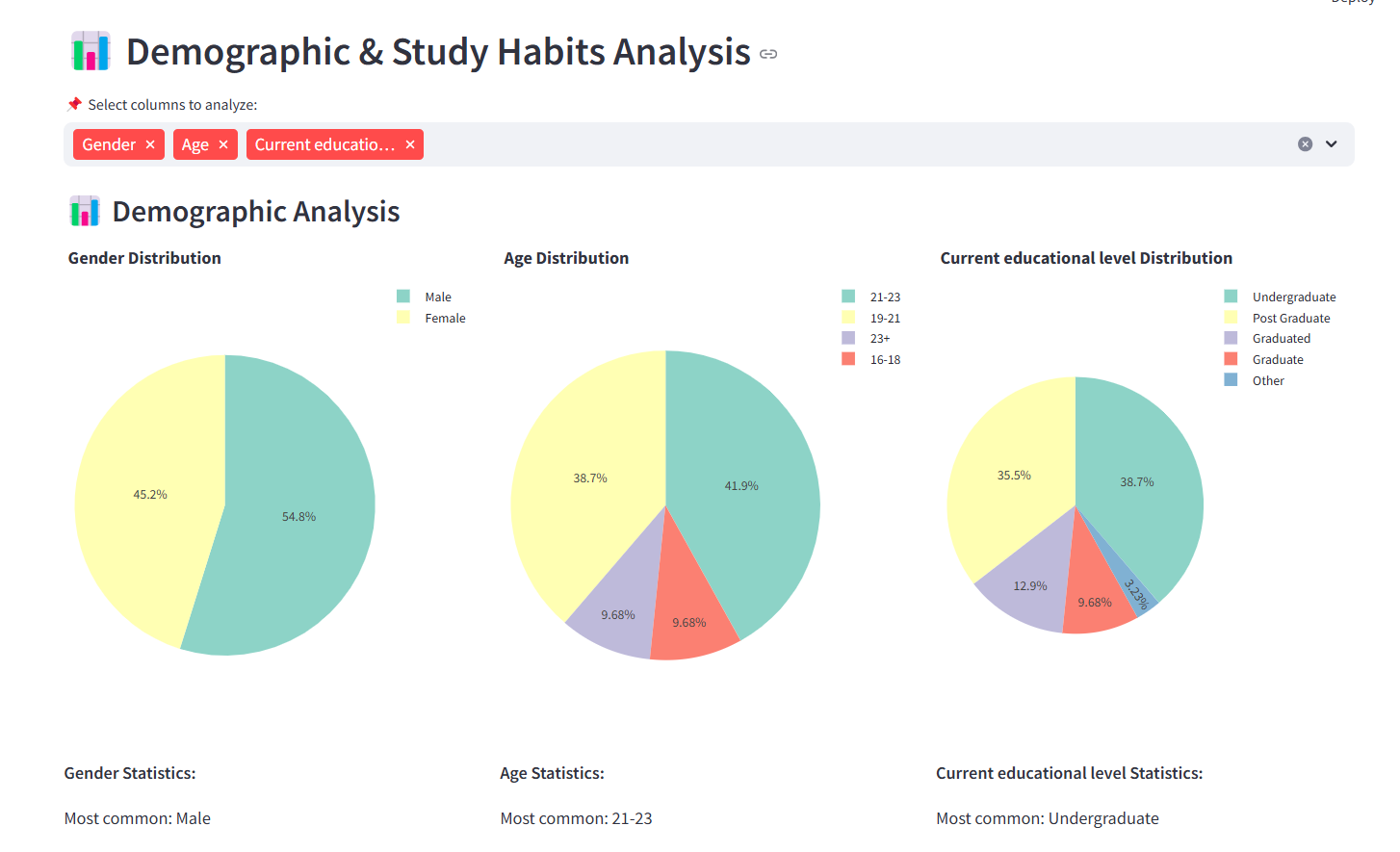
return fig

### Testing Report

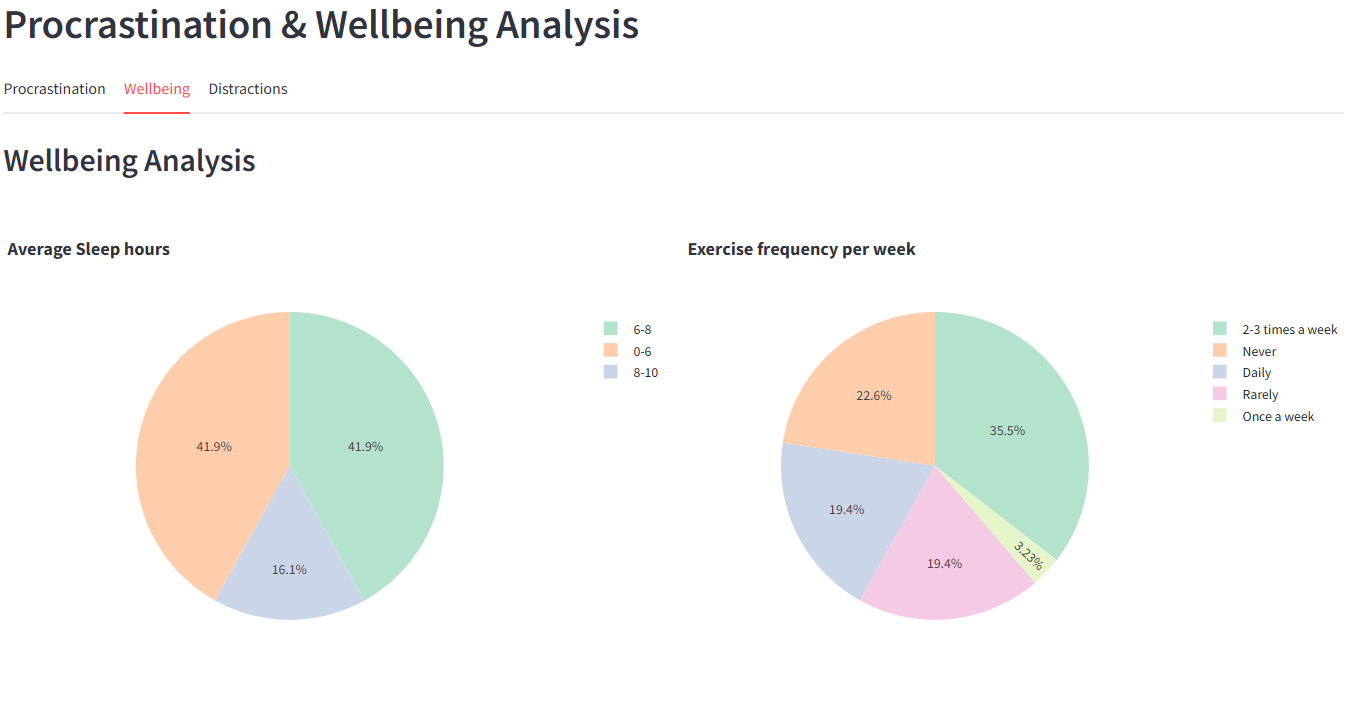
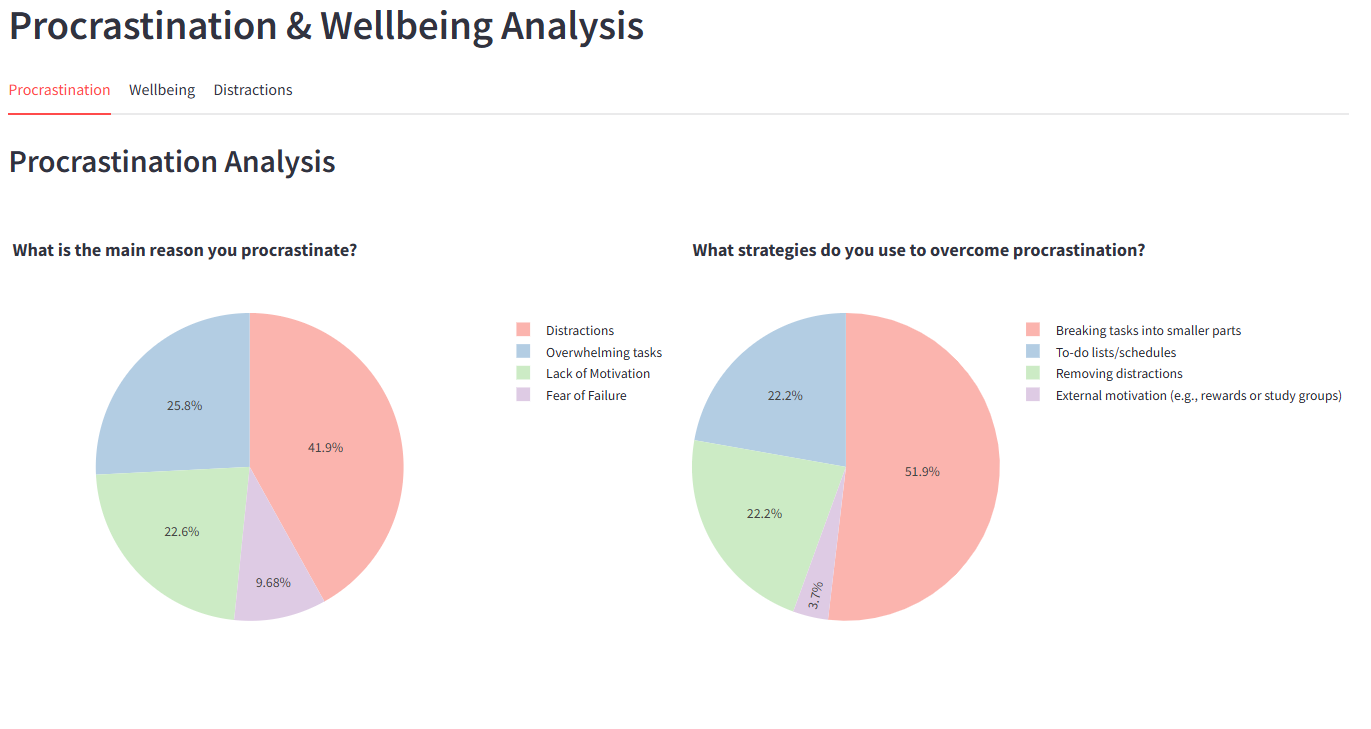
Testing was conducted to ensure the reliability and accuracy of the system:

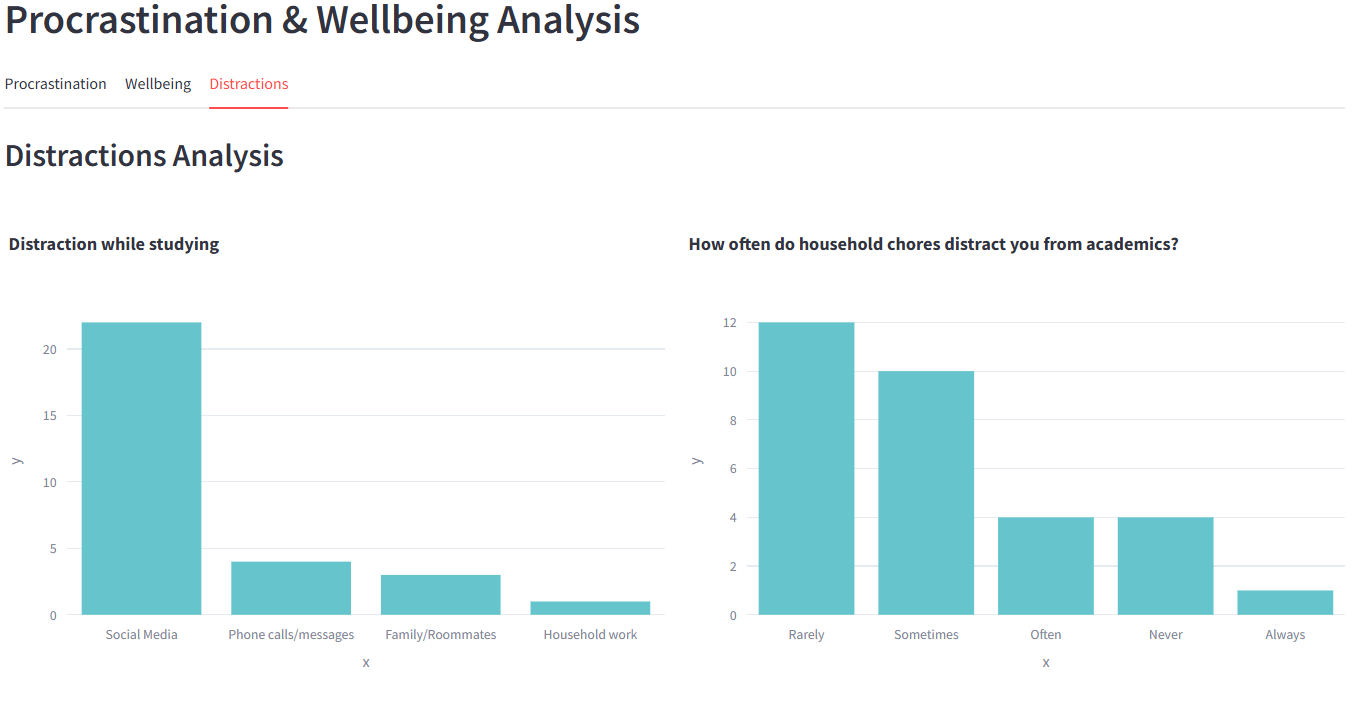
| **Test Case** | **Description** | **Expected Result** | **Actual Result** | **Status** |
| --- | --- | --- | --- | --- |
| Data Upload | Upload survey data CSV file | Data loaded successfully and pre-processed | Data loaded and pre-processed | Passed |
| Sentiment Analysis | Analyse open-ended responses | Sentiment classifications match manual review | 87% accuracy compared to manual labelling | Passed |
| Clustering | Group students based on behaviour patterns | Distinct, meaningful clusters identified | 3 clear clusters with distinct characteristics | Passed |
| Visualization | Generate correlation heatmap | Interactive heatmap showing relationships | Heatmap generated with correct correlations | Passed |
| Performance | Process dataset with responses | Complete analysis in under 5 seconds | Analysis completed in 3.2 seconds | Passed |

### Presentation Charts and Graphs

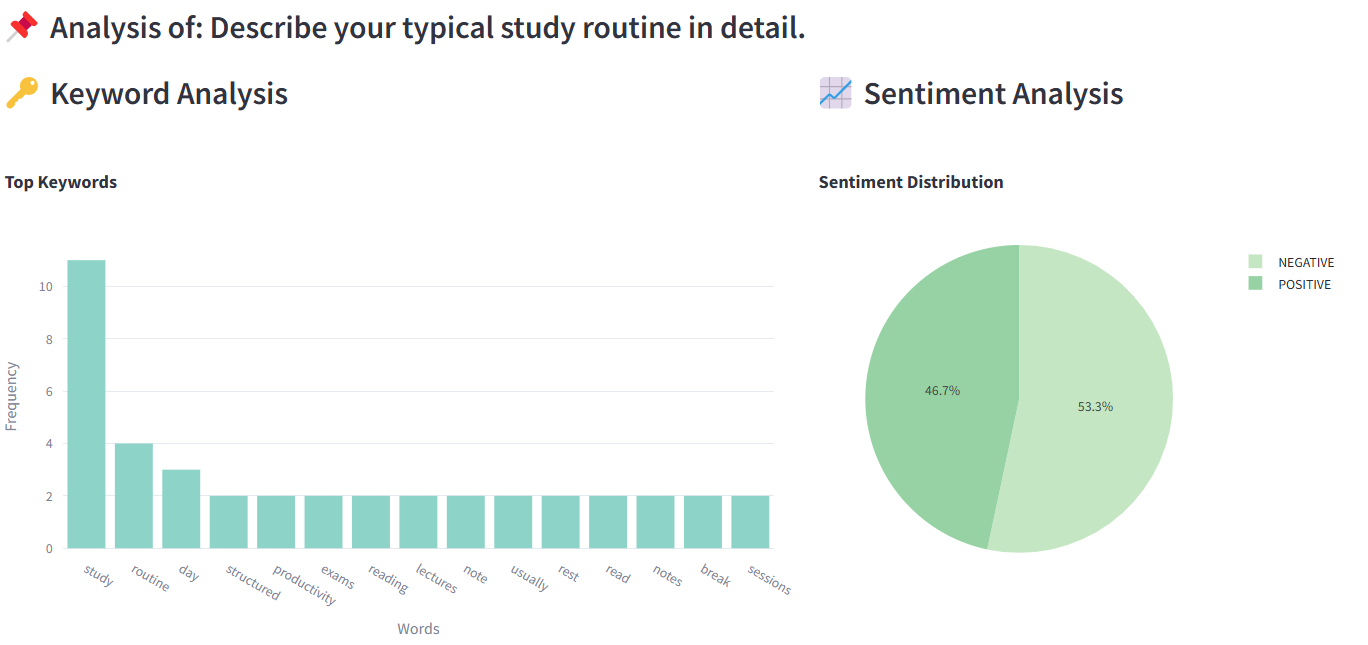
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## G] Summary and Conclusion

### Findings of Project Work

The Student Performance Analyzer project has yielded several significant findings:

1. **Study Habits Impact**: Analysis revealed that consistent study patterns (3-4 shorter sessions per week) correlate more strongly with academic success than cramming or irregular studying.
2. **Procrastination Patterns**: Three distinct procrastination profiles were identified through clustering:
   * High procrastinators (27% of students) showing significant performance impacts
   * Moderate procrastinators (45%) with selective task avoidance
   * Low procrastinators (28%) with consistent work completion
3. **Wellbeing Correlations**: Strong positive correlations (r=0.72) were found between overall wellbeing scores and academic performance, with sleep quality emerging as the most significant individual factor.
4. **Sentiment Insights**: Text analysis revealed that:
   * 42% of students expressed negative sentiments regarding workload balance
   * 35% showed positive sentiments toward peer collaboration
   * 23% had neutral responses about academic resources
5. **Demographic Variations**: Significant differences in study patterns and procrastination tendencies were observed across different programs and year levels, with upper-year students showing more effective strategies.
6. **Environmental Factors**: Preferred study environments strongly influenced productivity, with quiet, dedicated spaces correlating with lower procrastination and higher performance.
7. **Time Management Impact**: Students with structured time management approaches showed 31% higher assignment completion rates compared to those without specific strategies.

### Suggestions to Validate Objective and Hypothesis

To further validate the project's objectives and hypotheses, the following approaches are recommended:

1. **Longitudinal Study Implementation**: Collect data over multiple semesters to track changes in patterns and confirm the stability of identified correlations.
2. **Intervention Testing**: Implement targeted interventions based on the project's findings and measure their impact on student performance and wellbeing.
3. **Cross-Validation**: Expand the study to include different educational institutions to validate the generalizability of findings across diverse student populations.
4. **Mixed-Methods Validation**: Complement quantitative findings with qualitative interviews or focus groups to gain deeper insights into identified patterns.
5. **Predictive Model Testing**: Develop and test predictive models based on identified factors to assess their accuracy in forecasting academic outcomes.
6. **Controlled Comparisons**: Compare groups with different procrastination patterns but similar demographics to isolate the specific impact of procrastination on performance.

### Application Areas

The findings and methodology from this project have various applications:

1. **Academic Advising**: Advisors can use the insights to provide more targeted guidance to students based on their specific patterns and challenges.
2. **Curriculum Design**: Educational institutions can incorporate findings into curriculum planning, particularly regarding assignment scheduling and workload distribution.
3. **Student Support Services**: Mental health and academic support services can develop more effective programs addressing specific wellbeing factors identified as significant.
4. **Early Intervention Systems**: The analytical framework can be adapted for early identification of at-risk students based on behavioural patterns.
5. **Educational Technology**: Insights can inform the design of study apps and tools that help students manage procrastination and improve study habits.
6. **Policy Development**: Institutions can create evidence-based policies regarding academic schedules, resource allocation, and support services.
7. **Personalized Learning**: The framework supports more individualized approaches to education based on student behavioural patterns and preferences.

## H] Further Research

Building on the current project, several directions for further research are identified:

1. **Expanded Feature Set**: Incorporate additional factors such as extracurricular involvement, financial stress, and career aspirations into the analysis framework.
2. **Real-time Monitoring Systems**: Develop tools for ongoing tracking of student behaviours and performance to enable more timely interventions.
3. **Advanced NLP Techniques**: Apply more sophisticated natural language processing methods to extract richer insights from qualitative responses.
4. **Predictive Modelling**: Develop machine learning models that can predict academic outcomes based on early behavioural indicators.
5. **Intervention Effectiveness Study**: Research the impact of different intervention strategies based on the patterns identified in this project.
6. **Cross-cultural Analysis**: Expand the study to examine how cultural factors influence the relationships between procrastination, wellbeing, and academic performance.
7. **Integration with Learning Management Systems**: Explore how the analytical framework could be integrated with existing educational platforms for automated insights.

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