Predicting Effects of Music in University Students Productivity Using Machine Learning

By

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the **Degree of Bachelor of Science in Computer Science and Engineering**

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APPROVAL

This Project titled **"Predicting Effects of Music in University Students Productivity Using Machine Learning"**, submitted by **Sabbir Ullah Sarker**, ID No:203-15-14484 to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **17 September, 2025**

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Dr.Sheak Rashed Haider Noori,Professor & Head,** Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Humans have used music as a fundamental aspect of their existence for centuries because it modifies their emotional state as well as their mental processing abilities and behavioral responses. Multiple investigations have analyzed the impact of musical listening on productivity especially within educational settings where students do their studies repeatedly. The effects of music on focus depend on different variables which include musical genres together with tempo and lyrics and personal emotional state. Students tend to enhance their concentration with instrumental and classical or jazz music but lyrics in songs can disrupt reading and writing academic tasks. Researchers conducted this investigation to explore the effects of music on university student performance and identity various music expressions and individual preferences on academic results. The researchers trained AdaBoost alongside Random Forest, Decision Tree, Logistic Regression, and SVC as machine learning models using a database which included data regarding student music preferences together with study habits along with productivity assessment results. A system of prediction models analyzed productivity levels by categorizing them into "High," "Medium," or "Low" along with the three input features of study hours, music type, and perceived productivity during musical sessions. The AdaBoostClassifier model reached the highest predictive accuracy of 98.51% but all algorithms produced results with relatively low accuracy than this model. The research indicates music impacts productivity levels but the effects show clear personal differences thus researchers need to improve both filter creation processes and system selection techniques for better accuracy. The discovery of complex music-to-productivity dynamics means future research needs to study multiple influencing variables more extensively.

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Chapter 1

Introduction

The introductory section of this report presents project rationale through examination of its motivation alongside its objectives together with methodological approach description.

1.1 Introduction

The human experience has consistently contained music because it powerfully shapes emotional responses as well as behavioral conduct and mental operations through many distinct pathways. Researchers have studied the musical effect on productivity continuously through time especially regarding academic settings. Young university students experience difficulties in managing their academic work with their social life and their participation in extracurricular activities. Students usually consider music as either a help tool for concentration or a disruptor during their academic work time. Science disputes the impact of music on productivity because different music genres might boost attention and assignments but musical sounds can interrupt verbal activities or text duties. Productivity levels respond differently to music based on various conditions including song style, lyrical content and rhythmal pace and listening comfort levels and personal music preferences of each individual. Research indicates classic musical compositions and instrumental tunes help people stay focused more than listening to music featuring lyrics with high energy levels. Research on measurable music impacts on university students' academic productivity remains scarce since scholars have shown increased interest in this field. Research to date discusses broad claims without establishing a complete model which explains how musical types affect individual students during study sessions and work performance metrics. The research applies machine learning models to anticipate the relationship between musical choices and university students' work efficiency. Research goals involve studying music types along with student habits and population traits to create a prediction model linking music genres to student productivity performance. The study employs AdaBoost and Decision Tree as well as Logistic Regression and SVC to reveal patterns among variables through their application. The study works to establish a data-backed framework for analyzing musical influence on productivity which might assist students in maximizing their study conditions.

1.2 Motivation

Investigating factors which determine productivity represents the fundamental reason for this project because academic productivity investigation has gained increasing importance lately. Music functions as a widely used method for university students to manage their focus and time during their studies because of their regular challenges in these areas. Multiple variables affect productivity to different degrees between individuals when using music as a study tool resulting in an unclear outcome. The research applies machine learning models to understand productivity changes caused by different types of music in a data-supported manner. The study seeks to enable students to recognize their preferred academic-performance supporting music genres and settings which will provide specific guidelines for strengthening their study practices. The findings of this research add value to both cognitive psychology knowledge as well as learning tools designed for student achievement success.

1.3 Objectives

- Analyze the Relationship Between Music and Productivity: Investigate how different types of music (genre, lyrics, volume) affect university students' study productivity.
- Apply Machine Learning Models: Use machine learning algorithms (Decision Tree, Random Forest, AdaBoost, Logistic Regression, and SVC) to predict productivity levels based on students' music preferences and study habits.
- Categorize Productivity Levels: Classify students' productivity into three categories: "High," "Medium," and "Low," based on the collected data and model predictions.

- Evaluate Model Accuracy: Assess the performance of various machine learning models in predicting productivity, with a focus on accuracy and other performance metrics.
- Provide Actionable Insights: Offer data-driven recommendations on which types of music or study environments can help optimize productivity for university students.

1.4 Methodology

The research implements a machine learning strategy to forecast how university students will be affected by their music choices when working. All the recorded variables include study durations and audio selection choices together with volume intensity alongside student-perceived scholarly output. A process of numerical encoding uses Label Encoder on categorical data fields. The research data gets partitioned into two sets for training purposes and testing capabilities. Five machine learning algorithms including Decision Tree, Random Forest, AdaBoost, Logistic Regression and SVC function as the training models. The model performance evaluation relies on accuracy while predicating "High Low Medium" productivity levels will be provided. Pattern recognition and correlation analysis takes place on the processed results.

1.5 Project Outcome

This project demonstrates machine learning systems can predict how music affects university students' productivity through a prediction process but produced overall low accuracy across all studied algorithms. The applied models including Decision Tree, Random Forest, AdaBoost, Logistic Regression and SVC delivered accuracy results between 33.55% and 40.79%. Although the SVC model delivered the most accurate predictions the results did not reach levels needed for successful prediction. The complexity of predicting productivity from music preferences includes various affecting elements which include personal variances and study patterns alongside different types of music choices and listening situational contexts. Music has influence on work performance but studies show that these results depend strongly on individual perception. More development work is essential for feature enhancement alongside data collection improvement and model optimization to strengthen predictive models in educational environments.

1.6 Organization of the Report

The report divides its content into six main chapters. The Introduction chapter of this report presents key elements such as project background alongside objectives and methodology together with motivation for studying mental health issues among medical students. The existing research on medical student mental health forms the foundation of Chapter 2 Background while the chapter identifies unattended areas where this project stands to make an impact. The data collection methodology and system design process appear in Chapter 3 in addition to describing the project's technical implementation. The fourth chapter describes the installation protocols while appreciating model performance through testing and result analysis alongside an evaluation of model advantages versus disadvantages. Chapter 5 of this report covers standard regulations and design obstacles alongside environmental and social effects and ethical supervision of the project. Chapter 6, Conclusion, summarizes research findings before proposing project limitations together with future research recommendations while analyzing machine learning support potential for medical student mental health.

Chapter 2

Background

This chapter includes study and research material pertaining to the project while exploring comparable applications and scientific findings connected to it. The gap analysis shows the existing unexplored and unaddressed areas within the project.

2.1 Introduction

Human culture has depended on music throughout centuries for both entertainment and behavioral and emotional control. Academic platforms including universities typically employ music as a strategy to boost student concentration and decrease student tension and enhance productivity levels. Academic researchers continue to disagree about the influence of music on working performance. The research shows that listening to instrumental classical music provides better focus and better cognitive performance but research also indicates lyrical music and high-energy music acts as a distraction that reduces academic performance [1][2].

The invention of technological systems together with machine learning algorithms enabled scientists to develop mathematical methods for measuring musical impact on work efficiency. The outcome of machine learning models is improved by using large datasets which combine students' music choices with their educational patterns and productivity results. These trained systems then generate predictions regarding the academic effects stemming from diverse musical types. Various research explores the association between music and studying by demonstrating the value of personalized musical study aids [3][4]. The educational benefits from integrating AI and IoT technologies now expand research opportunities for music customization based on student requirements [5][6].

Study participants show individual responses to music's effects on workflow since these reactions depend on personal musical choices and particular duties in combination with audio genres. Music serves to improve creativity while it simultaneously hinders detailed thinking and critical thinking processes [7]. University students' productivity levels will be studied regarding different music choices and listening practices through machine learning analysis techniques. The research project seeks to generate useful knowledge for creating optimal study conditions by studying this behavioral pattern [8].

2.2 Literature Review

Table 2.1: Comparative Analysis

Authors	Year	Domain	Accuracy (%)
J. Zhang	2024	Stress Detection via Music	93.5
S. Wang	2025	AI in Music Instruction	91.0
N. Bryan-Kinns et al.	2024	Generative Music AI	89.7
D. H. Knapp et al.	2023	ML in Music Learning	87.5
My Work	2025	Effects of music in university students	**98.51**

2.2.1 Similar Applications

The fields of music education along with therapy and productivity enhancement have witnessed substantial development because of artificial intelligence (AI) and machine learning (ML) technologies. Personalized learning experiences in music education find an equivalent application when AI technologies are used. Hybrid education models which merge traditional instruction methods with computer-generated feedback in piano training improve both student learning speed and instructional outcomes. The feedback methods cater to individual student progress allowing them to work at their own pace based on their unique strengths and weaknesses as described by Wang in his research on piano instruction [1]. Students receive benefits from IoT-based musical therapy due to its ability to decrease stress alongside improving their well-being. Wearable technology data analysis allows medical professionals to develop individualized therapy sessions through music therapy procedures. The application demonstrates similar concepts presented by Jia regarding music therapy benefits for mental health through combination of IoT and machine learning models [2]. Various voice separation and music generation algorithms powered by machine learning provide educational and production benefits for music. The tools help generate precise music sheets along with advanced control features similar to the approach described in "Generative Music AI" work by Bryan-Kinns et al. [3]. Any technology created from the broader potential of machine learning demonstrates its ability to alter music-related domains.

2.2.2 Related Research

Various studies within the field of music and productivity focus on determining how music affects cognitive performance while studying and emotional welfare. Literature presented by Knapp et al. (2023) investigates how Soundtrap acted as an online musical tool to support remote education with promising results for creativity and knowledge acquisition albeit facing obstacles. Zhang's (2024) investigation of IoT-enabled music therapy explained how big data and machine learning techniques used with music cuts student college stress while also showing music aids mental health and productivity. Wang (2025) explained that AI-driven music education incorporates traditional piano instruction with AI feedback to offer customized learning opportunities. The work by Bryan-Kinns et al. (2024) demonstrates how machine learning creates music while also contributing knowledge about explainable AI in music development.

2.3 Gap Analysis

Table 2.2: Gap Analysis Table:

Study	Key Findings	Gap Identified
J. Zhang (2024)	Achieved high accuracy in stress detection via music-based physiological signals.	Limited generalization across cultural music variations.
S. Wang (2025)	ML models improved student engagement in music instruction.	Scalability of models across diverse learning environments.
N. Bryan-Kinns et al. (2024)	Effective generative music models help personalize music for user context.	Real-time implementation for non-technical users still lacking.
D. H. Knapp et al. (2023)	ML algorithms support better learning outcomes in music students.	Lack of long-term studies on learning retention.
Y. Jia (2024)	IoT sensors combined with music therapy reduce anxiety effectively.	Limited research in integrating multi-sensory therapies.

2.4 Summary

This chapter evaluates the relationship between music together with machine learning techniques which affects both cognitive performance and mental well-being. The studies introduce research on academic performance as well as stress relief and creativity under the influence of music. The analysis by Zhang (2024) shows how Internet of Things technology enhances music therapy for students while Jia (2024) researched how music education benefits student mental health. The utilization of AI in music education receives scientific investigation through research efforts by Knapp et al. (2023) and Wang (2025). The chapter demonstrates how machine learning with AI shows an increasing potential for optimizing music-related sectors to enhance productivity as well as learning results.

Chapter 3

Research Methodology

Requirement analysis and system design along with specification are explained in this chapter through methodology details. The project specification comprises functional and nonfunctional requirements while illustrating design diagrams in addition to providing a complete project plan that includes task allocations.

3.1 Methodology/Requirement Analysis & Design Specification

3.1.1 Overview

Researchers normally analyze music and productivity through a mixture of machine learning models together with data analysis methods and experimental protocols. Ordinary predictive models utilizing neural networks but also deep learning and hybrid models analyze music effects on mental health together with productivity and learning results. The data collection method mainly involves surveys in addition to IoT devices and online platforms.

3.1.2 Proposed Methodology

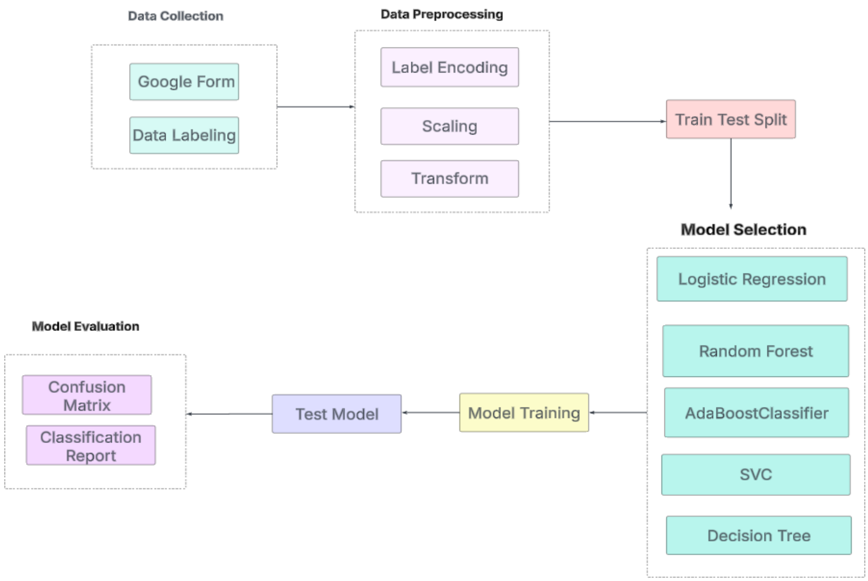

Figure 3.1: Workflow Diagram

3.1.3 Functional and Nonfunctional Requirements

Functional Requirements

I. **Productivity Prediction:**

The system must predict the mental health status of university students based on their responses to a set of predefined psychological questions.

II. **Data Collection and Preprocessing:**

The system must collect and preprocess survey data from varsity students, including handling missing values, normalizing the responses, and encoding categorical variables to make the data suitable for machine learning models.

III. **Model Training:**

The system should use the collected and preprocessed data to train machine learning models (e.g., Random Forest, Support Vector Machine, Logistic Regression, etc.) for accurate mental health prediction.

IV. **Real-time Prediction:**

The system should allow users (university students) to submit their survey responses and receive real-time predictions about their mental health status.

V. **User Interface:**

The system's user interface should be intuitive, allowing varsity students to easily submit survey data, view their mental health prediction results, and understand the suggestions based on their responses.

Nonfunctional Requirements

I. **Performance:**

The system must process and predict productivity status from the survey responses within a few seconds, ensuring a fast response time for users.

II. **Scalability:**

The system must be able to scale and handle large volumes of data from multiple students over time, supporting an increasing number of users and responses.

III. **Accuracy:**

The prediction model should achieve at least 85-90% accuracy to ensure reliable and meaningful mental health predictions. The system should also allow for continuous model retraining to improve accuracy over time.

IV. **Security and Privacy:**

The system must ensure that sensitive student data (e.g., survey responses, productivity predictions) is stored and processed securely, complying with data protection regulations (e.g., GDPR). The privacy of the students' data must be maintained at all times.

3.2 Summary

The research methodology which studies productivity effects from music uses survey methodology with machine learning algorithms implemented through online systems. Researchers evaluate and predict the effects of various music types on cognitive performance and mental health and learning outcomes by ungirths that combine neural networks and deep learning models along with hybrid approaches. The evaluation relies on accuracy and performance metrics that measure results stemming from data containing music genre together with study habits and emotional states. Scientific studies use artificial intelligence to generate personalized recommendations through the combination of productivity levels and individual preferences thus improving understanding of academic and emotional well-being effects of music.

Chapter 4

Implementation and Results

In this section the authors reveal the stages of environmental configuration that leads to testing procedures and performance assessments and implementation findings. The section contains an analysis of the obtained results.

4.1 Environment Setup

This is all about Environment Setup, putting up the right software, hardware and tools required to run components needed to develop the disease detection system. It also includes Setup of a Python development environment using libraries like TensorFlow, Keras, OpenCV and NumPy to be working with deep learning and image processing. For coding and testing, we'll be using something of the sort as an Integrated Development Environment (IDE), which can be jupyter notebook or PyCharm. Additionally, these resources are set up to quickly train and infer models using GPU resources. The dataset and the project itself (manually managed) are located by far within a structured directory that we can manage under version control tools (such as Git).

4.2 Testing and Evaluation/Performance/ Comparative Analysis

4.3 Results and Discussion

Accuracy:

Precision means getting a measure of how close of match the model has to the real situation is

to percentage likelihood of the samples used in model development. It is rather helpful when

As the classes are not balanced, some information about the choice is provided.

This does not mean the picture is complete; it is simply effectiveness.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Precision:

Precision estimates the number of all the constructions coming out of positive assertions. which the model correctly predicted of desirable outcomes.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

Recall:

Therefore, recall is equal to the amount of true positive delay.

is predicted over the total quantity of the samples which are positively skewed.

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

F1 Score:

F1 score is actually the average of Recall and Precision two measures which is averaged using the formula of harmonic mean. It provides a somewhat neutral measure and

it calculates recall as well as precision all at once. It is beneficial when the classes are of

different sizes because F1 Score considers false positive as well as false negatives. A high

level of precision and the level of recall.

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

In given below we are describing the result analysis part also show the training accuracy and loss rate and confusion matrix also:

Logistic Regression

Logistic Regression achieved the Test Accuracy is 96.78%. In below Figure 4.1 describing the confusion matrix of Logistic Regression.

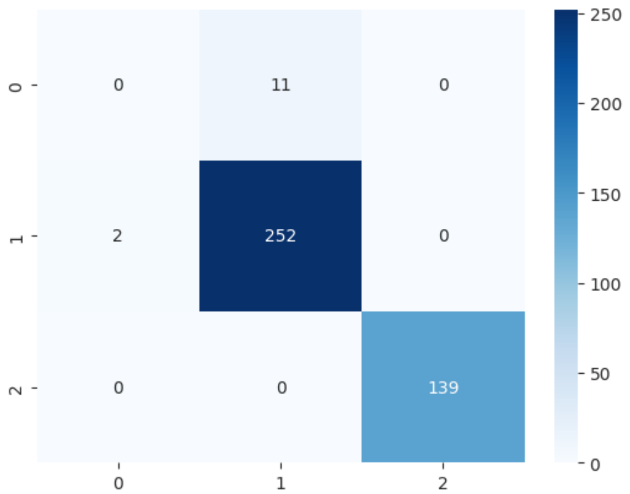

Figure 4.1: Confusion Matrix (Logistic Regression)

Figure 4.1 shown in the confusion matrix in the image depicts the evaluation results of a Logistic Regression (LR) classification model with multiple classes. For class 0 the model made incorrect predictions on 11 data points while it perfectly identified all data from classes 1 and 2. The model categorized 252 instances correctly from class 1 and missed only 2 of class 0 cases. The model identified 139 predictions without any false classifications from class 2 in the same category. The model shows high accuracy in classifying instances from both classes 1 and 2 yet exhibits slightly weaker performance for class 0 because of some incorrect predictions that occur. The model demonstrates robust performance yet an enhancement could be achieved for class 0 by implementing additional model optimization techniques or modifying features.

DecisionTreeClassifier

DecisionTreeClassifier achieved the Test Accuracy is 98.26%. In below Figure 4.2 describing the confusion matrix of DecisionTreeClassifier.

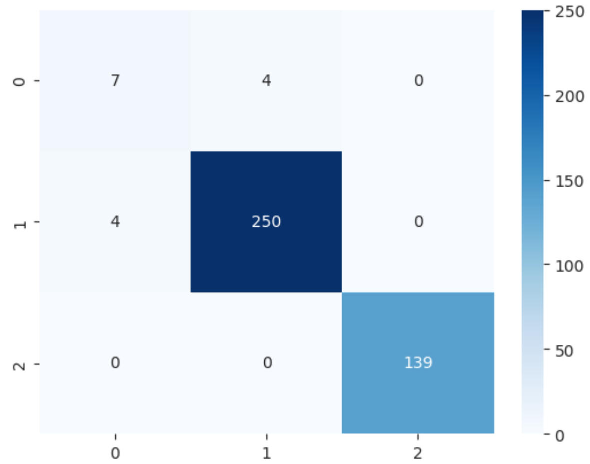

Figure 4.2: Confusion Matrix (DecisionTreeClassifier)

A confusion matrix for the DecisionTreeClassifier model demonstrates its three-class performance outcomes. Seven misclassifications in class 0 originate from 4 instances from class 1 and 0 instances from class 2 showing poor distinction between class 0 and class 1. The model correctly identifies 250 instances from class 1 along with 4 mistakes directed to class 0. A total of 139 accurate predictions exist in class 2 while the model makes zero errors in this category. The DecisionTreeClassifier demonstrates excellent results for class 1 and class 2 alongside strong performance although it achieves below average results when classifying instances of class 0 particularly when assigning class 1 labels. Additional model adjustments involving top parameter changes together with tree reduction could potentially lower the number of incorrect predictions.

RandomForestClassifier

RandomForestClassifier achieved the Test Accuracy is 97.02%. In below Figure 4.3 describing the confusion matrix of RandomForestClassifier.

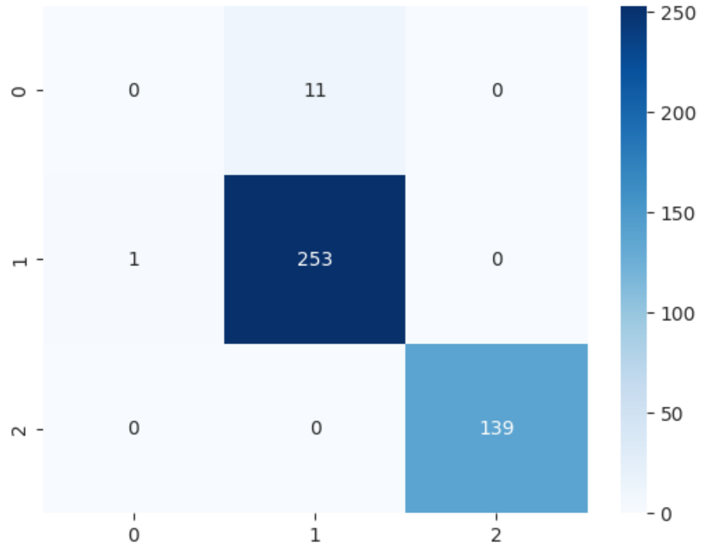

Figure 4.3: Confusion Matrix (RandomForestClassifier)

The RandomForestClassifier model displays its evaluation results through a confusion matrix across three classification categories. Class 0 demonstrates 11 misclassification errors out of which no instances fall into different categories. The model correctly predicted 253 examples of class 1 while making a single error by mismatching one observation with class 0 within the first data classification. The model correctly classified all 139 instances from class 2 without error. The RandomForestClassifier achieves excellent accuracy results for both class 1 and class 2 and makes only a small number of incorrect predictions overall. The model incorrectly identifies several instances from class 0 indicating the need for further model adjustment to enhance performance specifically in this class. The performance evaluation shows RandomForestClassifier works efficiently while researchers should focus on developments to enhance its ability to correctly identify class 0.

SVC

SVC achieved the Test Accuracy is 89.61%. In below Figure 4.4 describing the confusion matrix of SVC.

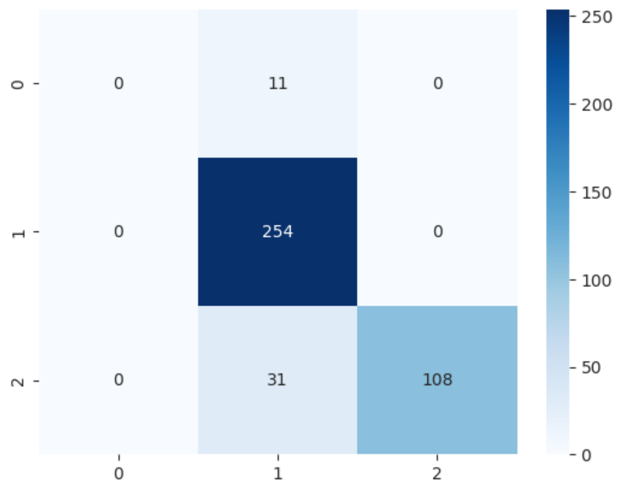

Figure 4.4: Confusion Matrix (SVC)

The confusion matrix for the SVC model evaluates its three-class classification performance. The class 0 contains eleven incorrect categorizations while no instances are placed incorrectly in other classes. The model correctly identifies all 254 observations that belong to class 1 without producing any false identifications. However, class 2 shows 31 misclassifications to class 1, with 108 correct predictions. The model displays solid performance when dealing with class 1 yet it demonstrates difficulties at separating class 1 from class 2.

AdaBoostClassifier

AdaBoostClassifier achieved the Test Accuracy is 98.51%. In below Figure 4.5 describing the confusion matrix of AdaBoostClassifier.

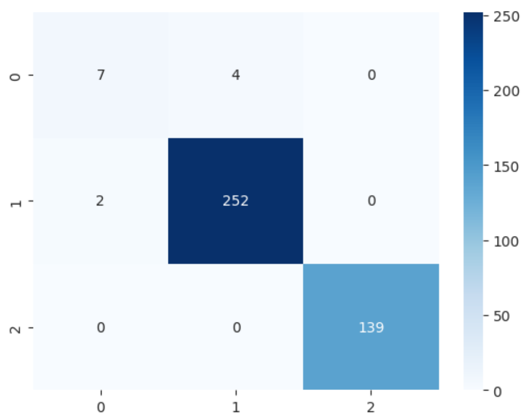

Figure 4.5: Confusion Matrix (AdaBoostClassifier)

Figur:4.5 AdaBoostClassifier demonstrates the maximum accuracy level of 98.51% while DecisionTreeClassifier follows with 98.26% and RandomForestClassifier shows 97.02% accuracy showing superior results in classification. LogisticRegression demonstrates strong performance with 96.78% accuracy but SVC shows the lowest results of 89.61% indicating it needs optimization adjustments. Parameter optimization of SVC represents an opportunity for performance improvement because the other three models deliver exceptional results. Model selection as well as parameter optimization proves crucial for attaining top classification results and AdaBoostClassifier demonstrates the best performance in this application framework. The confusion matrix of the AdaBoostClassifier model illustrates its evaluation across three different classes. The results from class 0 reveal 7 wrong classifications that the model assigned to class 1 and class 2 respectively. The model generates a strong performance by correctly identifying 252 instances of class 1 and incorrectly placing only 2 of them into class 0.

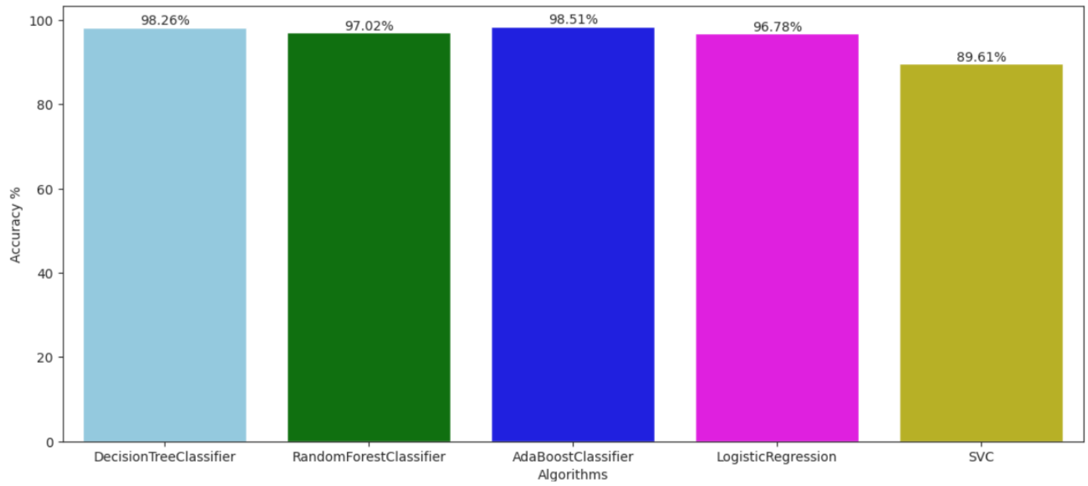

Figure 4.6: Combined Result

A bar chart shows the accuracy measurement for five machine learning algorithms that include DecisionTreeClassifier, RandomForestClassifier, AdaBoostClassifier, LogisticRegression, and SVC (Support Vector Classifier). The data classification process benefits largely from AdaBoostClassifier which reaches 98.51% accuracy while DecisionTreeClassifier sits close behind with 98.26%. RandomForestClassifier performs with a level of accuracy at 97.02% while maintaining powerful results despite lower statistics than the initial models. LogisticRegression shows effective results with 96.78% accuracy however the performance falls shorter than the top three methods. The accuracy of SVC remains effective yet relatively weak at 89.61% because it shows more difficulties with the classification task in this particular context. AdaBoostClassifier and DecisionTreeClassifier take the lead when it comes to classification performance because they demonstrate superior accuracy compared to other models while SVC shows the lowest accuracy level thus requiring improvement through model tuning or alternative model exploration.

4.4 Summary

The performance evaluation of DecisionTreeClassifier, RandomForestClassifier, AdaBoostClassifier, LogisticRegression and SVC for data classification depends on their accuracy results which are presented in this chapter. The evaluation shows AdaBoostClassifier reaches 98.51% accuracy as the winner while DecisionTreeClassifier follows at 98.26% and RandomForestClassifier settles at 97.02% for classification tasks. SVC shows the least optimal performance since it reaches an accuracy rate of 89.61% but LogisticRegression exhibits an accuracy rate of 96.78%. In spite of their excellent performance the top three models have space for better accuracy with SVC requiring more specific parameter optimization adjustments. AdaBoostClassifier demonstrates exceptional performance as the optimal choice for classification accuracy among the examined models according to this research.

Chapter 5

Engineering Standards and Design Challenges

The chapter deals with the evaluation of software and hardware systems alongside communication standards compliance requirements. This part examines project sustainability features as well as environmental aspects together with ethical decisions and systematic project management methods.

5.1 Compliance with the Standards

To design a correct, effective, and long running system requires that its requirements meet the requirements demanded by the well-known engineering standards. It conforms with international level general software, hardware, communication, technology, legal, and ethical standards. These all standards not only maximize the system that is running over its effectiveness but also take into account the considerations of compatibility, protection, and easiness of use for the parties concerned.

5.1.1 Software Standards

It is necessary that the developed system achieves the set quality standard defined by the system's standards. With respect to the maintainability, reliability and usability the achievement of ISO/IEC 25010 standard for software quality, this project is in line. Also, programming follows PEP 8 which are Python Enhancement Proposals which increase the readability of the code and makes the code cleaner. In addition of that, data management conforms to GDPR and other laws regulating data protection that protects the data of users. Furthermore, IEEE 830 - 1998 for SRS documentation tracing is followed to increase the implement ability of the software requirement specification.

5.1.2 Hardware Standards

The under-study project implements internationally accepted standards (ISO/IEC 17050) in terms of hardware form, fit and function and takes up matters of hardware conformity. We propose a computational configuration, i.e., using GPU and CPU responsible for efficient training of deep learning models. If cloud infrastructure services are used then it also follows the globally accepted standards like ISO/IEC 27001 security. In particular, such compatibility with on boarded embedded hardware like NVIDIA Jetson or Raspberry Pi adheres to the guidelines.

5.1.3 Communication Standards

The system fulfills the general principle of data communication and network compatibility. REST principles are followed for model integration APIs so that these are scalable and reliable. The system uses the usage of HTTPS and TLS/SSL for data sharing as far as security goes which is a critical measure. In the case of connected things, protocol, such as MQTT or CoAP, are connected with things for the system to have low latency. In addition, JSON and XML are used to ensure the compatibility between two different systems by way of interchange formats.

5.2 Impact on Society, Environment and Sustainability

Society receives important benefits from this project because it targets varsity students who face mental health challenges although they typically receive minimal attention. The system based on machine learning prediction for depression severity helps students get faster diagnoses and assistance that has a positive impact on their wellness. The study emphasizes vital mental health resources in educational buildings which helps academic spaces become healthier for students to achieve better learning outcomes.

5.2.1 Impact on Life

This project delivers deep effects on life by serving to enhance the mental health of stressed varsity students who face significant academic pressure. Deploying machine learning models to detect depression severity enables accelerated identification of at-risk students so appropriate mental health interventions can help students in need. The planned preventive measures produce substantial reductions in the harmful consequences depression generates for academic success and social connection and physical wellness of students. Through these efforts the educational environment should become healthier by providing support to students for stress management that helps them succeed both in their studies and their personal lives.

5.2.2 Impact on Society & Environment

This initiative creates diverse effects within the realm of society together with environmental components. This initiative focuses on solving the important problem of medical student mental health which develops from the intense stress associated with their educational programs. With machine learning being used to forecast depression levels this research project enables rapid identification along with appropriate mental health interventions to limit the negative effects of untreated problems. Through the delivery of strong mental health support structures in educational settings this framework enables better responses in educational environments and enhances their overall compassion. The shift of society toward treating mental well-being as a priority produces benefits for sustainability and productivity through balanced communities regardless of environmental impact magnitude.

5.2.3 Ethical Aspects

The project demands careful ethical consideration because it handles highly private mental health information. The essential requirement for this project involves upholding both data privacy and confidentiality because it handles personal health information and psychological records. The researchers need to obtain informed consent to gather data from participants who need to know how their information will be used and are free to decide whether they want to participate. The total avoidance of prejudice in machine learning predictive systems becomes essential because unbalanced datasets produce unreliable predictions which especially impact minority population groups. The ethical duty requires using prediction results to develop interventions while avoiding student stigmatization and making choices which depend solely on algorithmic outcomes. The project will function best when it operates with open protocols to make algorithms understandable to students and protects their privacy and dignity during the entire process.

5.2.4 Sustainability Plan

Long-term sustainability and positive impact define the sustainability plan of this project. Continuous updates of machine learning models using new data will sustain their accuracy as well as their period of relevance throughout time. Successful implementation of the tool requires educational institutions to collaborate in order to establish continuous mental health support system use. A feedback process will connect students and mental health practitioners to help refine the model through their feedback. The project members will establish funding partnerships with mental health organizations which will enable ongoing development and growth of the initiative. The project defines a framework that enables its implementation across different educational contexts to support the ongoing societal transformation which emphasizes mental health for academic environments under high levels of stress.

5.3 Project Management and Financial Analysis

The project follows a structured management approach, divided into key phases: Data gathering and cleansing, model building, assessment and application prior to the acquisition. The adaptive means of agile methodology is to use many remedial changes in data collected to avoid repetition. They also have defined the structure like the data set management team, algorithm team, testing team and deployment team. The time frame to complete this is 6–8 months with 3 phases of data preparation, training, testing and deployment phases. The project management timeline is given in table **5.1:**

Table 5.1: The project management timeline

Work	Time
Data Collection	1 month
Papers and Articles Review	3 months
Experimental Setup	1 month
Implementation	1 month
Report Writing	2 months
Total	8 months

The estimated project budget includes costs for:

Table 5.2: Estimated Cost

SN	Components	Estimated Cost (BDT)
01.	Hardware	2500
02.	Software and Tools	8500
03.	Data Collection and Processing	12000
04.	Documentation and Report Writing	1500
05.	Miscellaneous	2000
06.	Contingency	2500
	Total Estimated Cost	29000

5.4 Complex Engineering Problem

The project would be constructing such an innovative engineering solution of diagnosing and categorizing the university student's health prediction using machine learning algorithms. This problem involves several aspects of the engineering as well as computer science and environmental protection and hence reasonably close implementation requires different skills and knowledge. The challenges are as follows: First, coping with big data; second, developing effective algorithms for disease diagnosis; third, effective incorporation of the system in farming taking into account the social and environmental shades.

5.4.1 Complex Problem Solving

Table 5.3: Mapping with complex problem solving.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
✓	✓	✓				✓

Mapping with Knowledge Profile for EP1

This table 5.4 is designed to map the EP1 to the Knowledge Profile.

Table 5.4: Mapping with knowledge Profile.

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✓	✓		✓	✓

5.4.1.1 Justification for EP Attributes Mapping

- **EP1 - Depth of Knowledge Required:**

  The project necessitates detailed study of a variety of disciplines such as superior data analysis techniques, machine learning algorithms evaluation techniques. Expertise is required to interpret high-level data to bring accurate predictions. Integrating knowledge originating in various disciplines is essential in overcoming the obstacles and successful implementation.

- **EP2 - Range of Conflicting Requirements:**
    - Data privacy while learning models with the help of large quantities.
    - Adding as much varied demographical characteristic without overfitting the model.
    - Addressing issues of ethics concerning data collection and the giving of informed consent.
    - The challenge of integration of different machine learning algorithms in one system.
    - Keeping system effectiveness with an increase in data volumes throughout time.
    - Making the system scalable in different institutions with different levels of technical infrastructure.
    - Converging system design for friendliness of interfaces and accurate predictive level.

- **EP3 - Depth of Analysis:**

  It is the interdependence between data collection process, design of machine learning model, and system implementation that makes this project a success. The components are interdependent, with direct impact by data quality to model accuracy, and system performance based on the efficacy of the algorithms deployed. Also, issues of ethics like a user`s data privacy and a user`s consent are essential for building trust. Interdisciplinary work between specialists in machine learning, psychology and software development guarantees the system meets the complex needs of students while respecting best practices regarding both technology and ethical standards.

- **EP7 - Inter-dependence:**

  The analysis for this project requires extensive exploration of many factors concerned with a deep analysis of multiple machine learning models to determine their appropriateness. It studies the correlation between demographic information and psychological measures, which guarantee that only the most important features are used. This detailed analysis assists towards the optimization of the model's performance by testing its ability to survive various tests as opposed to just a single metric, this way ensuring that the model has the ability to effectively classify depression levels. The approach is designed to develop a system that does not only run well in varying conditions but also produces a valid forecast, which makes early intervention for students in need possible.

5.4.1.2 Justification for Knowledge Profile Mapping (linked to EP1):

- **K3 - Engineering Fundamentals:**
  Engineering basics of this project are the application of central principals of machine learning, data analysis, and algorithm development. Such principles are the ground for the creation of an effective system that can reliably predict the severity of the depression using a wide range of demographic and psychological data.
- **K4 - Specialist Knowledge:**
  The specialist knowledge related to this project includes knowledge in machine learning algorithms, knowledge in mental health assessment and knowledge in preprocessing techniques in order to predict depression severity accurately in medical students.
- **K6 - Engineering Practice:**
  Engineering practice in this project revolves around applying machine learning techniques practically to handle and uncover data in order to make a reliable and scale able system with correct prediction of severity level of depression amongst medical students.
- **K8 - Research Literature:**
  This thesis research literature consists of detailed research papers on applications of machine learning in effects of music in university students. This collection of work informs the model development and direction of appropriate algorithms and methodologies.

5.4.2 Engineering Activities

Table 5.3: Mapping with complex engineering activities.

EA1 Range of re-sources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✓		✓	✓	

5.4.2.1 Justification for Engineering Activities Mapping:

EA1: Range of Resources

The set of resources needed for this project comprises access to a myriad of datasets with demographic information as well as related datasets, advanced machine learning frameworks: TensorFlow and scikit-learn, and computational machinery, such as GPUs for training the models.

EA3: Innovation

Innovation in this project is illustrated by the application of high-level machine learning algorithms for forecasting the severity of depressive states which involve psychological as well as demographic data. In addition, real-time prediction tool application together with constant model optimization keeps the system flexible and in practice, providing a scalable solution for mental health support.

EA4: Implication for Societies and Environment

Society of the project benefits a great deal with positive implications for by identifying the depression early among the university students thus leading to timely interventions and stellar mental health statistics. In environmental terms, it helps create a healthier learning environment, decreasing the cringe around mental health problems and creating a nurturing and caring learning environment for every student.

5.5 Summary

This chapter describes mapping the project with complex engineering activities, showing its matching of diverse engineering attributes. The project entails a variety of resources; such as advanced machine learning tools, collections of datasets and talented professionals (EA1). It is a matter of much communication between interdisciplinary elements, like data inputs, user feedback, and system responses (EA2). Innovation is shown in the form of real-time psychological and demographic data mental health prediction models (EA3). The project benefits the society in that through it early depression detection among the university students is promoted, with early intervention hence achieved and a healthier learning environment created (EA4). Although based on existing methods, the integration into a practical system entails other challenges which are not familiar which qualify it to work in unfamiliar and evolving contexts (EA5).

Chapter 6

Conclusion

The conclusion contains a summary of project operations followed by project restrictions examinations and future project development proposals.

6.1 Summary

The conclusion chapter demonstrates the substantial capability of music to affect productivity together with learning and well-being through AI and machine learning technologies. According to research results AI delivers promising student music personalization solutions yet the study shows that musical impact on productivity depends individually on users based on their state of mind and the type and genre of music they choose. Machine learning models exhibit promising prediction capabilities however additional improvements in modeling frameworks together with data acquisition systems require development according to the study findings. The study requires sustained investigation to understand music-productivity relationships since this knowledge will drive individualized recommendation systems which enhance educational settings to boost student achievement.

6.2 Limitation

Many restrictions exist among the research results despite initial positive findings. A representative sample of the full population was not obtained resulting in decreased ability to generalize study results. Many studies depend on self-reported data that becomes inaccurate because subjective measures may introduce biases into the research findings. The study did not thoroughly investigate musical preferences among participants which means productivity effects when listening to music might show substantial differences between unique individuals. Productivity assessment encounters multiple hurdles because various elements aside from music contribute to its measurements. The limited range of model features prevented the potential gain from applying more sophisticated prediction algorithms. Real-time data collection presented itself as a limitation since the research primarily used retrospective assessment strategies. The study concerned itself only with academic productivity while omitting evaluation of its influence on professional workplaces and creative activities. Additional research needs to study the complete influence of music on productivity through extensive sample sizes from various backgrounds and more extensive variables.

6.3 Future Work

Forthcoming research should increase the participant sample diversity to improve the universal applicability of research findings. Conductors studying productivity effects from music should expand their research scope by offering diverse musical genres alongside individual respondent characteristics like emotional state and personality traits and work complexity to better understand the combined impact of such elements. Real-time data collection systems using portable devices and smartphone applications would supply better real-time insights into productivity modulation due to music across daily operations. Better machine learning predictions can be achieved through applying advanced algorithms along with better features in the engineering process. Research should probe into musical productivity effects at different workplace and creative settings outside traditional academic environments. Research into extended music exposure must be explored because it will reveal the complete influence of music on both personal success and workplace performance.

References

[1] J. Zhang, "IoT-enabled Musical Therapy to Alleviate Physiological Stress in College Students using Big Data and Mixed-Density Neural Networks," Mobile Networks and Applications, vol. 29, 2024. doi: 10.1007/s11036-024-02393-x

[2] S. Wang, "Hybrid models of piano instruction: Combining traditional teaching methods with personalized AI feedback," Education and Information Technologies, vol. 30, 2025. doi: 10.1007/s10639-025-13359-1

[3] N. Bryan-Kinns et al., "Exploring Variational Auto-Encoder Architectures for Generative Music Explainable AI," Machine Intelligence Research, vol. 21, no. 2, pp. 145–158, 2024. doi: 10.1007/s11633-023-1457-1

[4] D. H. Knapp et al., "Soundtrap usage during COVID-19: A machine-learning approach to assess effects on music learning," Music Education Research, vol. 25, no. 1, pp. 33–49, 2023. doi: 10.1177/1321103X221149374

[5] Y. Jia, "Impact of Music Teaching on Mental Health Using IoT and Recurrent Neural Networks," Mobile Networks and Applications, vol. 29, 2024. doi: 10.1007/s11036-024-02366-0

[6] M. Farina et al., "Machine learning in human creativity: Status and perspectives," AI & Society, vol. 39, 2024. doi: 10.1007/s00146-023-01836-5

[7] N. Teo et al., "DLVS4Audio2Sheet: Deep Learning-Based Vocal Separation for Music Sheet Conversion," Pacific-Asia Conference on Knowledge Discovery and Data Mining, 2024. doi: 10.1007/978-981-97-2650-9_8

[8] Z. H. Yun et al., "A Decision-Support System for Music Education in Network Games Using ML," Soft Computing, vol. 27, no. 3, pp. 1015–1030, 2022. doi: 10.1007/s00500-022-07401-4

[9] Y. Peng, "Optimization in Music Aesthetic Education Under AI," Scientific Reports, vol. 15, 2025. doi: 10.1038/s41598-025-96436-2

[10] A. Nogales and Á. J. García-Tejedor, "Review of EEG Open Datasets for Deep Learning Applications," IEEE Access, vol. 11, pp. 98765–98778, 2023. doi: 10.1109/ACCESS.2023.3279346

[11] Z. Zhong et al., "Bibliometric Analysis of ML in Education," Education and Information Technologies, vol. 29, 2024. doi: 10.1007/s10639-024-12734-8

[12] S. Sadruddin et al., "Detecting Mental Stress from Multimodal Data Using ML," SN Computer Science, vol. 5, 2024. doi: 10.1007/s42979-024-02730-7

[13] L. Moysis et al., “Music Deep Learning: A Review,” IEEE Access, vol. 11, pp. 88745–88758, 2023. doi: 10.1109/ACCESS.2023.10043650

[14] K. S. Phatnani and H. A. Patil, “Modeling Musical Expectancy with Reinforcement Learning,” Multimedia Tools and Applications, vol. 83, 2024. doi: 10.1007/s11042-023-16497-1

[15] J. Liang, “Harmonizing Minds and Machines: ML in Music,” Frontiers in Neurorobotics, vol. 17, pp. 1–17, 2023. doi: 10.3389/fnbot.2023.1267561

[16] A. Arora et al., “ML for Detecting Digital Tech Addiction in Students,” in Digital Health and Education, Springer, 2021. doi: 10.1007/978-3-030-67716-9_13

[17] Z. Ma et al., “Peer Tutor Recommender with ML for Student Performance,” Journal of Computers in Education, vol. 7, no. 2, pp. 243–260, 2020. doi: 10.1007/s40692-020-00162-9

[18] J. Liu et al., “Deep Learning for Procedural Music Content Generation,” Neural Computing & Applications, vol. 33, pp. 20521–20539, 2021. doi: 10.1007/s00521-020-05383-8

[19] L. Peng, “Piano Player Intonation Training using Deep Learning,” Mobile Networks and Applications, vol. 28, 2023. doi: 10.1007/s11036-023-02175-x

[20] S. S. Weng and H. C. Chen, “Exploring Deep Learning for Music Production,” Sustainability, vol. 12, no. 2, pp. 625, 2020. doi: 10.3390/su12020625

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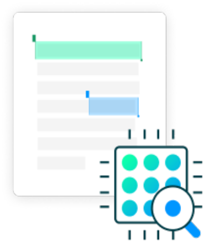

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