# DEVELOPMENT OF A LEARNING ADAPTABILITY SYSTEM FOR MTU STUDENTS USING A DEEP LEARNING ALGORITHM

**By**

**SOJEBE, OLOLADE ADEOLA**

**18010301053**

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## DECLARATION

I hereby declare that this project has been written by me and is a record of my own research work. It has not been presented in any previous application for a higher degree at this or any other University. All citations and sources of information are clearly acknowledged by means of reference.

SOJEBE, OLOLADE ADEOLA

Date

## CERTIFICATION

This is to certify that the content of this project '**Development of a Learning Adaptability System for MTU Students using a Deep Learning Algorithm'** was prepared and submitted by **SOJEBE OLOLADE ADEOLA** in partial fulfilment of the requirements for the degree of BACHELOR **OF SCIENCE IN COMPUTER SCIENCE.** The original research work was carried out by her under by supervision and is hereby accepted.

______________________________(Signature and Date)

Mr. J. A. Balogun

Supervisor

______________________________(Signature and Date)

Dr. M. O. Adewole

Coordinator, Department of Computer Science and Mathematics

## DEDICATION

I would like to dedicate this project to God Almighty, for being faithful and merciful, for seeing me through to the end of this project. I also dedicate this work to my father, Mr. Segun Sojebe and my mother, Mrs. Adeola Sojebe, for being a major source of support in every way.

## ACKNOWLEDGEMENTS

My sincere gratitude goes to the God who created all things and manifests himself in diverse ways than we can comprehend for his mercy, loving-kindness, and presence in the times I was in need. I also appreciate the entire staff and management of Mountain Top University for the immeasurable impact they have had on my life academically and spiritually from the person of the chancellor, Dr. D.K Olukoya and the chaplain. I specially recognize my supervisor, Mr. J.A Balogun for believing in me and pushing me to do more. I also recognize Dr. Funmilayo Kasali and a host of other lecturers who have made special contributions to the success of my academic pursuit. Finally, I duly appreciate my siblings, best friend, friends, and colleagues without whom this journey could not have been a success. May the God of heaven water your lives.

## ABSTRACT

The aim of this study is to adopt the use of deep learning algorithm for the development of a learning adaptability system which can be used for classifying students based on relevant information. The specific objectives are to identify existing studies, construct instrument of data collection, collect relevant data analyse the data collected and develop the model, implement the system based on the results and test the system. The study identified the various user and system requirements, specified the system design, and implemented the system.

A review of the literature was being done to identify and understand existing works, a structured questionnaire was constructed according to the Felder-Silver Model for collecting data from students of MTU, relevant data was collected from 600 students using a simple rando sampling technique, the collected data was analysed using a deep neural network architecture and the system was implemented using python.

The results of the system showed the implementation of the system's database with the use of data mining algorithm for the extraction of features from external environment and classification in order decipher whether a student learning style. Other systems have been built already, but some of these existing systems are expert systems, and are often complex and hard to relate with. Furthermore, they are not so accurate in their prediction and hence are not so reliable.

The system design was specified using UML diagrams, such are use case, sequence, and class diagram

**Keywords:** *Data mining algorithm, Mountain Top University, Information System, Learning Adaptability Systems*

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# CHAPTER ONE

# INTRODUCTION

## 1.1 Background of Study

The topic of learning means acquiring knowledge or skills through study, experience, or being taught. The need for this topic is that student should identify their various styles of learning in the institution. (Wikipedia, 2021)

According to Alkhasawe (2008), learning styles are individual characteristics that affect how students communicate with their professors, peers, and learning environment.

According to Fareeha Rasheed (2021), The way that kids learn is crucial in helping them retain information for longer periods of time and advanceperiodsal understanding. In both offline and online settings, questionnaires are used to determine learners' preferred learning modes.

The process of learning, educating, or training utilizing web-based technology is known as e-learning. E-Learning is becoming more economical in higher education as technology advances, yet it still faces a significant cost barrier in generating its resources. It has transformed the dynamics of educational material and offered new paths for education. Due to the COVID-19 pandemic's impact, e-learning has become increasingly popular due to its high temporal and geographic flexibility, low knowledge acquisition, and extensive learning resources.

Deep learning is one of the more recent technologies that have the potential to automate this process and result in successful smart e-learning. Deep learning with artificial intelligence is becoming increasingly popular, and it is having an impact on many aspects of eLearning. It provides future online learners with intuitive algorithms and automatic eLearning content delivery via modern LMS platforms. (Anandhavalli Muniasamy, 2020)

## 1.2 Statement of Problem

Traditionally, learning styles are mainly measured through surveys and questionnaires, where students are asked to self-evaluate their own behaviour. It has been gathered from human psychology that students perceive information in varying patterns. As a result of this, every student does not perceive learning in that same manner. This has prompted the need for lecturers to secure dynamic in the delivery of teaching styles and learning resources. Therefore, there is a need to adopt a data-driven model for the automation of the identification of the learning styles of students using relevant data, hence this study.

## 1.3 Aim and Objectives

The aim of this study is to adopt the use of deep learning algorithm for the development of a learning adaptability system which can be used for classifying students based on relevant information.

The specific objectives are to

i. identify existing studies
ii. construct instrument of data collection
iii. collect relevant data using (ii) above
iv. analyses the data collected in (iii) and develop the model
v. implement the system based on the results of (iv)
vi. test the system

## 1.4 Methodology of the Study

To fully accomplish the objective, the following methods were adopted.

a. a review of literature in the field of learning adaptability was conducted to identify existing works

b. a was constructed according to the Felder-Silver Model for collecting data from structured questionnaire students of MTU

c. relevant data was collected from 600 students using a simple random sampling technique

d. the collected data was analysed using a deep neural network architecture

e. the system was implemented using python

## 1.5 Significance of Study

This study is important because most students have a preferred way to learn; some learn best by listening, some must observe every step, while others must do it to learn it. The fact is that individuals need all three modalities to truly commit information to memory: visual, auditory, and kinesthetics'. While most are typically stronger in one area than another, the trick is figuring out the preferred modality and capitalizing on strengths. It's important to remember that everyone learns differently. Sometimes, parents make the mistake of thinking that their child learns as they do, but this is often not the case. Many adults learn well by auditory means, but children frequently need visual and kinesthetics' methods.

## 1.6 Scope and Limitation

The scope of this research is to predict student learning style, where features will be selected and categorized in four groups such as Active/Reflective, Sensing/Intuitive, Verbal/Visual and Sequential/Global with respect to Felder Silverman questionnaire, Learning Object, Behaviour, and dimension that cover student learning style pattern. Moreover, ANN classification data mining algorithms will be used for predicting student learning style.

### 1.7 Definition of Terms

Some of the technical words used in this study are defined here.

a. **Deep Learning:** It is also known as deep structured learning and is part of a broader family of machine learning methods based on the layers used in artificial neural networks.
b. **Machine Learning:** It is the scientific study of algorithms and statistical models that computer systems employ to complete a task effectively without requiring explicit instructions, instead relying on patterns and inference.
c. **Student:** Is a person who is enrolled in a school or other educational institution and is pursuing knowledge, developing professions, and obtaining employment in their chosen field.
d. **Data analysis:** It is a well-known term for the process of looking at, purifying, manipulating, and modelling data to find relevant information, draw conclusions, and assist in decision-making.
e. **Algorithm:** It's a clear description of how to tackle a class of issues including computation, data processing, automated reasoning, and a range of other tasks.
f. **Neural Network:** It's a neuronal network or circuit, or, in a more modern meaning, an artificial neural network made up of artificial neural neurons or nodes.

g. **Exploratory data analysis** is a method for evaluating data sets to highlight their key characteristics, frequently using visual techniques.
h. **Labels**: The predictions or forecasts you are making.
i. **Features**: The defining characteristics.
j. **Attributes**: Different data kinds, such as real, integer, nominal, or text, can be present in a column of data or attributes. There are various types of characteristics, features, and labels in supervised learning.
k. **System:** It's a collection of objects that work together as part of a mechanism or a network.

### 1.8 Organizing a thesis

This project's work was organized as follows: in Chapter two, input attributions for the prediction model were chosen based on a literature review; in Chapter three, the methods used in this study were introduced; in Chapter four, prediction results were presented and analysed; and finally, in Chapter five, the research work was considered for conclusion, recommendations, and potential future research directions were proposed.

# CHAPTER TWO

# LITERATURE REVIEW

## 2.1 History of Learning

According to Thorndike (1928), Learning is a permanent change in behaviour because of experience, and the behaviour includes both external and internal actions of the individual which are observed and remain unobserved by the outside world. It also includes the different ways in which people understand or experience or conceptualize the world around them. The phrase "learning styles" relates to the idea that people differ in terms of the type of instruction or study that works best for them. Learning-type assessment proponents argue that identifying each student's unique learning style and customizing education to it is necessary for effective instruction.

### 2.1.1 History of Learning Analysis

For comprehending and improving learning and the environments in which it takes place, learning analytics refers to the measurement, collecting, analysis, and reporting of data on learners and their circumstances. Due to the ability to collect and make student data available for study, online learning has grown significantly during the 1990s, especially in higher education. Clicks, navigation patterns, time spent on task, social networks, information flow, and concept development through discussions can all be monitored when students utilize an LMS, social media, or other online tools. Massive open online courses' (MOOCs') quick development provides researchers with extra data to assess teaching and learning in virtual environments.

### 2.1.2 History of Learning Styles

According to Farid, Abbasi (2014), The importance of learning style in helping students retain information for extended periods of time and deepen their conceptual comprehension. Though we could link the origins of learning styles to the philosophical underpinnings of learning, the emergence of LS may not be conditioned by philosophical influence because learning philosophies served as the foundation for learning theories, whereas learning styles are a by-product of learning theories (or educational theories at broader level). Differences between science and philosophy can also be used to illustrate it. It follows that while learning theories, whether at the macro or micro level, deal with philosophical explanations of the realities as they are based on evidence, learning styles are almost exclusively meso-level theories (or theories that are higher level than macro level theories but lower level than micro level theories)

### 2.1.3 Review of Learning Analysis

According to (Sendeyah Hantoobi, 2021), Learning Analysis is all about recognizing students' behaviours, academic performance, academic accomplishment, and other associated learning challenges, a new field called learning analytics has evolved. Numerous review studies were undertaken due to its extreme relevance and recentness. The behavioural, affective, cognitive, and metacognitive patterns of learning, however, have received most of the attention in earlier reviews. It has been noted that the reviews that have already been published have not examined the learning analytics studies through the prism of their categories.

## 2.2 Review of Research Approaches in Deep Learning

The gradual building of methods or devices for predicting student learning style has benefited from the work of many academics and scientists. Here, we list a handful, including the following:

a. Convolutional Neural Network (CNN)

b. Artificial Neural Network (ANN)

c. Regression (Linear and Logistic)

d. Support Vector Machines (SVM)

e. Data Mining

f. Naïve Bayes

g. Decision Trees

h. Anomaly Detection

## 2.3 Review of Relevant Literature

The minds and ideas of experts on the topic have been captured in a few related projects that have been worked on. To educate the public on how to accurately forecast student learning style, most of them employ scientific and intelligent methodologies. Below are some of these research articles that are discussed:

### 2.3.1 A Comparative Analysis of Preferred Learning and Teaching Styles

The model states that engineering instructors who modify their teaching methods to incorporate both poles of each of the specified dimensions "should come close to creating an optimal learning environment for most (if not all) students in a class" (Felder & Silverman, 1988, p. 675). According to Barber and Milone (1981), most people, especially those over the age of college, are visual learners, whereas most college instruction is verbal. Ernst and Clark (2008) note that while many researchers have examined how students use their preferred learning styles in lectures and lab settings, few have tried to connect their findings to teacher bias in the classroom. According to Bastable (2008), as opposed to surface learning that just calls for memorizing, material that is presented in a manner that corresponds to the students' learning styles encourages understanding, which results in the retention of new information at a conceptual level (Wittmann-Price & Godshall, 2009). When students can choose knowledge and arrange it into representations that make sense to them, they get the most out of it (Jonassen, 1999), (Mayer R. E., 1996), (Mayer & Moreno, 1998; Mayer, 1999b), (Wittrock, 1990). A study was done to see how well the instructor's teaching style and the students' chosen learning styles matched up in a materials process course to fill this stated requirement.

### 2.3.2 Prediction Learning Style Based on Prior Knowledge for Personalized Learning

(MS. Hasibuan, 2008) claims that the existing online learning paradigm still lacks the personalization necessary to meet learners' demands. There are currently two methods for the automatic detection of learning styles: data-driven and literature-based. The learners' interactions with the system provide as the foundational information for identifying their preferred learning style. The accuracy value for this system's learner engagement strategy is, however, only below 80%. Prior knowledge refers to the abilities and knowledge that learners are expected to possess and identify their preferred learning modes. This is thus because prior knowledge has four levels that are directly tied to learning style: knowledge of fact, knowledge of meaning, integration of knowledge, and application of knowledge. This study suggests a smart learning model that recognizes different learning methods based on existing knowledge. In this study, there are three phases: (a). Creating previous knowledge using the Weight Cosine Coefficient (WCC) technique for evaluation (b). Assessing each learner's past knowledge; the outcome of this assessment is referred to as Level of Knowledge (LOK), and the final step is the prediction of the learner's preferred learning method using mapping.

### 2.3.3 An Adaptive E-Learning System based on Student’s Learning Styles

To address the strategic plan of the Ministry of Education and Culture in Indonesia to modify the ratio of vocational secondary schools to be higher than the general school one, there is a strong demand for a positive instructional application, according to (Hariyanto, 2019). By considering the student's learning style and prior knowledge, this study provides an adaptable e-learning system. The students' accomplishment in terms of the three lowest levels in the cognitive domain (knowledge, understanding, and application) in the e-learning group is compared with the traditional classroom group to assess the efficacy of the suggested e-learning program. The usability evaluation based on the students' viewpoint and the connections between the elements listed in the usability questionnaire is another intriguing subject to investigate.

### 2.3.4 Online Adaptive Learning: A Review of Literature

To provide learners with tailored learning content, many e-learning systems now have tools that adjust learning materials to their needs. To help teachers generate pedagogical content and learning objects that are customized to each learner's skills, talents, and preferences, researchers from all around the world have worked on this problem. This study's goal is to review existing works and publications on adaptive learning in online learning environments. To be more precise, we have addressed several issues pertaining to the adapted object, the adaptation criteria, the adaptation parameters, and the adaptation methods or algorithms in online learning platforms. Additionally, this study will enable us to give a vision for the use of adaptation criteria and statistically characterize the promising research areas in online adaptive learning. 2020 (Jallal Talaghzi)

### 2.3.5 Predicting students' learning styles using regression techniques

Ahmad Mousa Altamimi (2022) claim that customization is necessary in online learning since there is little interaction between students and teachers and because each student has a unique learning style. Several works have suggested utilizing categorization approaches to identify learning styles. However, when students have a variety of learning styles or no dominating style, the present detection algorithms are rendered useless. As a result, this study has two goals. The first step in determining the preferred learning style is to build a prediction model using regression analysis. Comparing regression models and classification models to find learning style is the second step. Based on data gathered from a sample of 72 student using the visual, auditory, reading/writing, and kinesthetic (VARK) inventory questionnaire, a series of machine learning algorithms have been constructed to root our conceptual model. The findings demonstrate that regression procedures, which thinking about the possibility of pupils having numerous learning styles with varying probabilities, are more accurate and indicative of real-world situations. This study, in our opinion, will assist educational institutions in incorporating different learning styles into their instruction.

### 2.3.6 Combining supervised and unsupervised machine learning algorithms to predict the learners' learning styles

(Ouafae EL AISSAOUI, 2019) asserts that to implement an effective adaptive e-learning system, a student model must be created that accurately captures all the student's characteristics. One such characteristic is learning style, which refers to the way in which a student prefers to learn. With the help of online usage mining techniques, machine learning algorithms, and the learners' current behaviours', we have presented a method in this work to automatically identify the learners' preferred learning styles. The log file that was taken out of the e-learning environment was pre-processed using web usage mining. The K-modes clustering technique was used to group the collected learners' sequences into 16 learning style combinations based on the Felder and Silverman learning style model. Then, a student's learning style was predicted in real time using the naive Bayes classifier. We used our method using a real dataset that was taken from the log file of an e-learning system, and we utilized the confusion matrix method to assess how well the classifier performed. The outcomes show that our strategy produces top-notch outcomes.

### 2.3.7 Adaptive e-learning systems through learning styles: A review of the literature

By utilizing modern equipment and leveraging technology, the field of education has advanced significantly. To give a uniquely created environment that meets the needs and requirements of the learner, the research focuses on tailored solutions. The learner model, adaptability module, and domain module are examined in this review, which was inspired by a survey of 42 publications released between 2015 and 2020. With a focus on the significance and effectiveness of the use of Learning Styles in the adaptive learning process, this review attempts to describe the theoretical and technological underpinning of Adaptive E-learning Systems. Researchers working in this area as well as upcoming designers and developers of adaptive platforms are the target audience for this literature review. (Iraklis Katsaris, 2021)

### 2.3.8 Predicting learners' styles based on fuzzy model

Marwah Alian (2017) is visual, auditory, kinesthetic, and read-and-write. Each type of learner primarily acquires knowledge by one of the three primary receiving senses, vision, hearing, or doing. The learning process and the success of the learner are impacted by the learner's learning style. It is preferable to choose a learning tool for the student based on his preferred method of learning. This study proposes a fuzzy model for predicting learner style based on student characteristics. A set of students were subjected to the system's testing, and the results from the online VARK questionnaire, a tool designed to instruct the students on how to maximize their learning were compared to the results. When compared to the VARK, the new fuzzy inference method produced categorization results that were 48% similar.

### 2.3.9 Adaptive e-learning environment based on learning styles and its impact on development students' engagement

Designing suitable adaptable e-learning environments helps to tailor instruction to reinforce learning objectives, according to (El Sabagh, 2021). Adaptive e-learning is considered as stimulus to assist learning and improve student engagement. This essay aims to construct an adaptive e-learning environment based on students' learning preferences and investigate how such environment affects participation. This study also tries to describe and contrast the suggested adaptive e-learning environment with a traditional e-learning strategy. The outcomes showed that the experimental group outperformed the control group statistically considerably. These experimental findings suggest that an adaptable e-learning environment may be able to motivate pupils to learn. The results and suggested adaptive e-learning strategy can aid e-learning institutions in creating more specialized and adaptive e-learning environments to boost student engagement.

### 2.3.10 Students' Perceptions of ILS as a Learning-Style-Identification Tool in E-Learning Environments

This essay evaluates the Felder-Silverman learning model's Index of Learning Styles, a tool for assessment. The subjective questionnaire and the Index of Learning Styles were used to collect data on students' preferred methods of learning for the analysis of the concurrent validity of the ILS. According to the findings, the cold-start issue can be solved by using the Index of Learning Styles to define learning style at the outset of the learning process. We circumvent the identified constraints of the Index of Learning Styles by extending the Protus user interface with new functionality that permits a free choice of the learning style during the learning process. Regardless of the used evaluation instrument, this solution might be employed in many personalized e-learning environments and result in a more accurate student model. (Zoran Marosan, 2022)

## 2.4 Summary

Knowledge discovery is fuelled by data analytics, which is based on predicting student learning preferences. It supports cutting-edge decision-making, such as assessing a student's learning preferences and forecasting an event before it happens. A decision made with knowledge is worth more than one made with calculated guesswork. The results of this study could be applied to the creation of applications that support decision-making. These programs will contribute to increasing resource efficiency and human benefit.

# CHAPTER THREE

# METHODOLOGY OF THE STUDY

## 3.1 System Analysis

System analysis is the stage of development where the current system is examined. It determines how the existing system can be improved and outlines the many conditions that must be met for those improvements to be implemented. It aims to provide answers to queries regarding the developed system, including what it will perform, where it might be used, and when it might be utilized. For this work's system analysis, we created an analysis strategy by researching existing systems and using student learning style prediction via an artificial neural network. We then gathered the specifications for the creation of the proposed system, drafted the system proposal at the conclusion of the analysis, and submitted it for review.

## 3.2 Review of Existing System

The current system is concerned with predicting a student's preferred learning style by matching it to those preferences and classifying it according to those categories using traditional methods, which are frequently stressful for both students and even the lecturer. In addition, other researchers applied data mining techniques on a collection of Felder Silverman learning style scores obtained from a questionnaire given to MTU students. They compared the results to see which technique had the best accuracy.

### 3.2.1 Problems with Existing System

Below are some of the issues with the current system.

a. Because there are many manual processes, students can't get outcomes right away.
b. Instead of researching various data cleaning and pruning approaches that prepare and make a dataset more suitable for mining, the prediction classification methodology for learning management has received greater attention.

### 3.3 Review of the Proposed System

The suggested system combines computer science, learning management systems, and statistics to produce a method that will go a long way toward making it simple to forecast a student's learning activities. Additionally, the system frequently employs both deep learning and data mining to predict this model.

#### 3.3.1 Justification for the Proposed System

The following are the justifications (benefits) of the suggested system:

a. The system has many opportunities in the school
b. To lower the percentage of students who enter school too early, which will boost the economy of the nation.
c. Users can discuss their learning preferences and receive immediate results.
d. Promotes awareness of the value of taking learning seriously and aids in educating both young and elderly about it.
e. As a secondary safeguard against learning style forecasting.

### 3.4 Functional Requirement

The functional requirements specify the functions of the software system and describe or explain the behaviour of the system. They also highlight the functions or, more precisely, the services that are anticipated of the proposed system to provide for its customers.

The following are the functional requirements for the proposed system.

i. Dividing the four sorts of learning styles
ii. The system must be able to receive input from users.
iii. The system must be able to collect information from users, and users and students can interact with it through an interface.
iv. The system must also be able to forecast the learning style (either graphically or in text form).

### 3.5 High level Model of the Proposed System

The figure that follows illustrates the structure of the predictive learning system and discusses the system's operations.

### 3.6 Data Flow Diagram of the Proposed System

The user of the system is depicted in the data flow diagram for the prediction of learning style system in Figure 3.2. When a user visits the application's homepage, he or she must log in to access the system. The user must register to access and make predictions if they are not already registered.

### 3.7 Methodology

The approach used to accomplish the goals of the suggested system is described in this section of the project. The CRISP-DM (cross-industry standard process for data mining) approach was chosen as the methodology for this project because it sequentially tackles the issue at hand.

In this piece of study, the following methodology will be shown:

i. Understanding the proposed model and having an idea of it
ii. Understanding the gathered data and its applicability to the proposed system
iii. Pre-processing of the data
iv. Model implementation
v. The model's effectiveness will be assessed using data sets gathered from the secondary health sector.

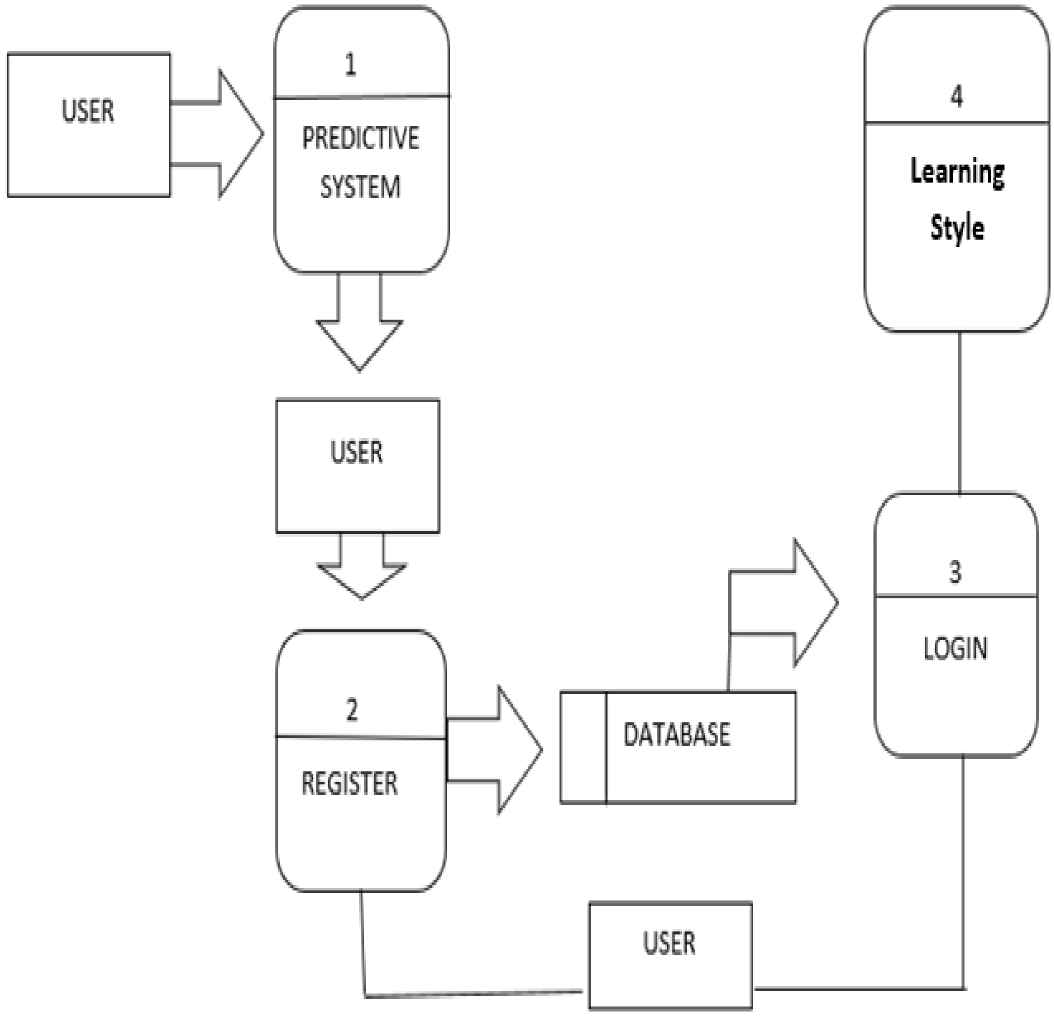


**Figure 3.1: Data Flow Diagram of The Proposed System**

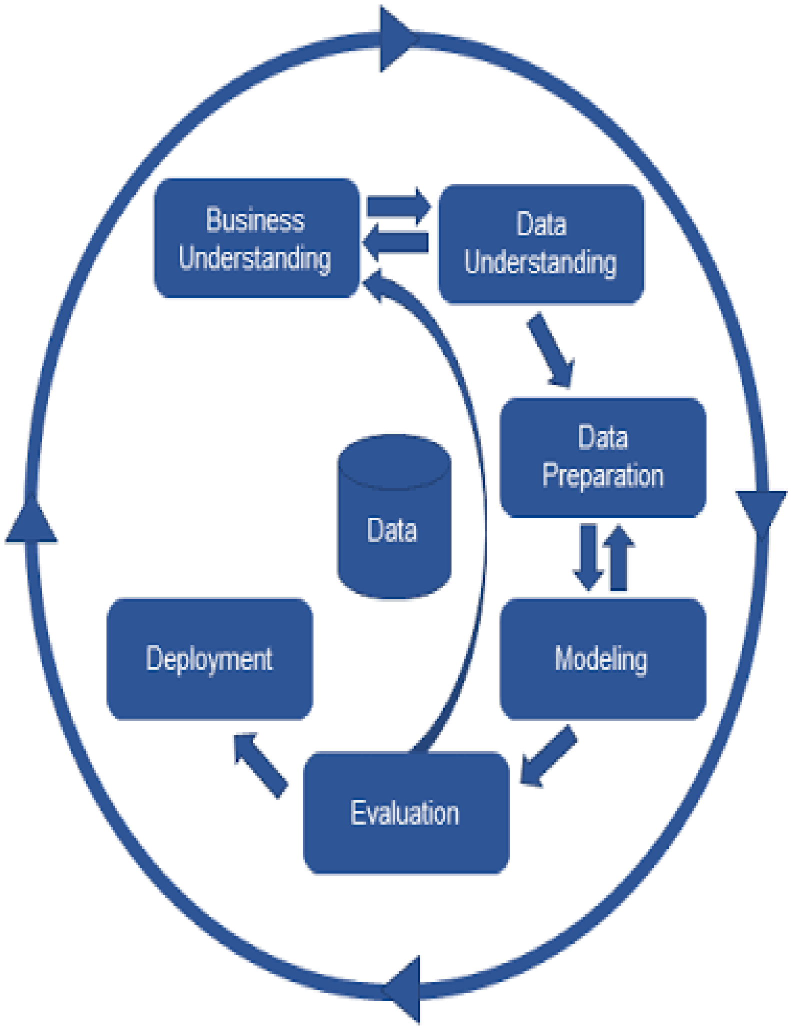


**Figure 3.2: Diagram of the proposed methodology**

### 3.7.1 A Brief Introduction to The Methodology

This research project uses the CRISP-DM (cross industry standard process for data mining) since it includes the stages required to complete the project's objective. According to study, the CRISP-DM has been used to predict diabetes and heart disease, among other health conditions. This supports the idea that using the methodology will enable us to produce the necessary model for this project.

# CHAPTER FOUR

# IMPLEMENTATION AND RESULT

To create a model for learner learning style prediction in relation to data mining categorization, this chapter explains the system design and execution of learner learning style using machine learning techniques. And from this idea come the following goals:

## 4.1 Objectives of the Design

i. To employ learner preference ILS (FSLSM styles, Felder and Silverman, index of questionnaire), which entails gathering data from undergraduate students (UGS) at Mountain Top University in Ogun state and separating the data in accordance with the needs of the prediction result.

ii. To pre-process the data to satisfy the classification model's requirements

iii. To categorize unknown new data using the training model that was created for learner learning prediction

iv. To store the train data set's model and use it for data mining classification.

v. Using a stored model with test data

vi. To make predictions about the outcome and calculate accuracy metrics using the test data set

vii. To assess the system's effectiveness.

The goals are the fundamental procedures for forecasting a data set in data mining, which is a subset of artificial intelligence (AI) approaches utilized in statistical methods to allow the machine to get better with practice. Therefore, artificial intelligence refers to any methods that allow a computer to replicate human behaviour (AI). The core focus of this study work is the AI that gives rise to the DM that offers the naming service (i.e., ensures that each piece of data in the platform has a unique name) and serves as the platform's authority.

### 4.2 Architectural Design of Learner Learning Style System

The process of determining the components that make up a system, as well as the framework for component control and communication, is known as architectural design. The software architecture that was created because of the design process was explained in this section. (Al-Sarayreh, 2021)

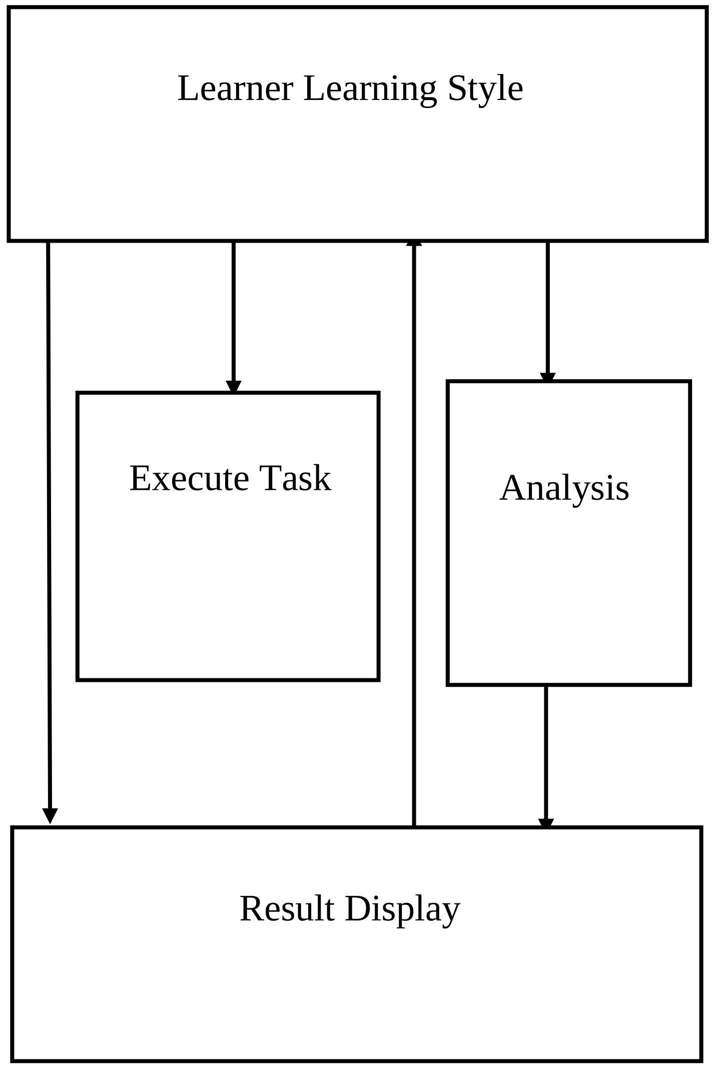


**Figure 4.1: Architectural Design of Student's Learning System**

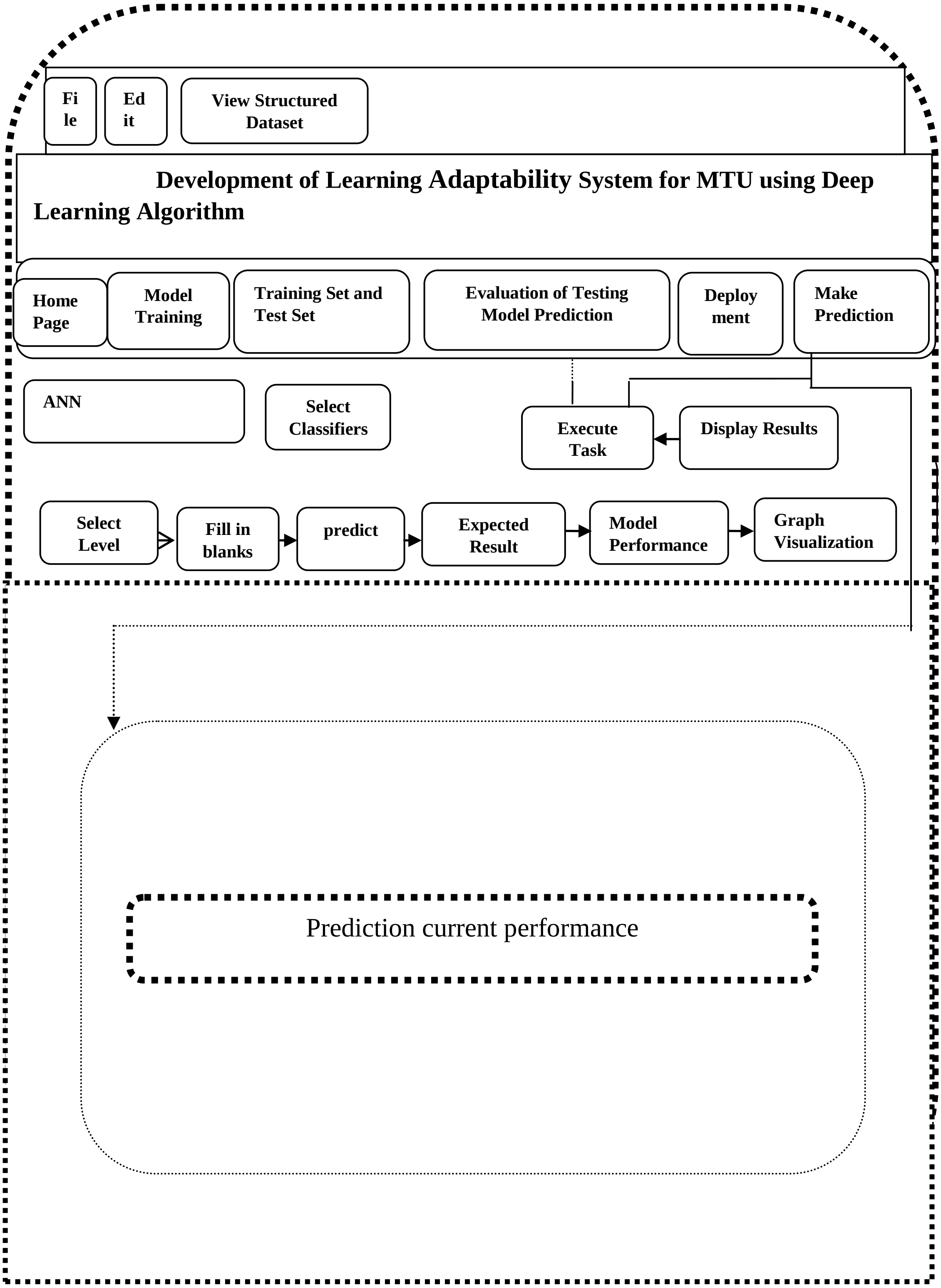


**Figure 4.2: System Design of Learner Learning System**

In Fig 4.2 to develop the Knowledge discovery in databases (KDD) design modelling regarding machine learning model, the sample dataset of the UGS student program from Mountain Top University had to be retrieved through the index of Learning style (ILS) record as well as demographic characteristics. This model was used to create a data mining model for predicting student attrition; each prediction task is handled differently by the model. The system has control menus with specific functions to carry out their tasks, such as the home page, Training Model, Training set and Test set, Evaluation of Testing Model, Deployment and Model Make Prediction, etc.

## 4.3 System Design

The goal of system design is to implement the modelled system. To accomplish the project's overall objective, the complex activity of system development is divided into more manageable sub-activities that interact with one another

### 4.3.1 Physical Design

The physical design is focused on the system's real input and output procedures. It focuses on the methods used to input, verify, process, and output data in a system. The system's requirements for carrying out or carrying out its operations, as well as the output that is the outcome of those activities, are specified in the physical design

### 4.3.2 Logical design

The abstract illustration of how data flows, inputs, and outputs of a system relate to the logical architecture of that system. It goes on to detail further operational features of the system that the user cannot see.

#### 4.3.2.1 Input/Output Format

The data set for this study, which was received from undergraduate students at Salem University Lokoja, Kogi State, and the outcome of previous students' records was taken from the college database faculties and students, is described by the input/output format. It is used to forecast the attrition of the current students in their upcoming semesters and is recorded in a different database. All the characteristics of the pupils that are observed in this system are shown in Table 4.1 below.

**Table: 4.1: The Research Variables for Supervised Machine Learning Algorithms to Predict Learner Learning Style**

| Gender | age | College | course_of_study | level | Q_1 | Q_2 | Q_3 | Q_4 | Q_5 | Q_6 | Q_7 | Q_8 | Q_9 | Q_ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 22 | 1 | IRPM | 3 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | |
| 1 | 21 | 1 | Business_Admin | 3 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 0 | 17 | 1 | Languages | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | | 0 | |
| 1 | 19 | 1 | Languages | 4 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | |
| 1 | 17 | 1 | Business_Admin | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | |
| 1 | 18 | 1 | Finance | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | |
| 1 | 19 | 1 | Accounting | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | |
| 0 | 18 | 1 | English | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | |
| 1 | 16 | 1 | Accounting | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | |
| 0 | 18 | 0 | Biology | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | |
| 1 | 17 | 0 | Microbiology | 4 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 0 | 18 | 1 | Economics | 4 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | |
| 0 | 19 | 0 | Microbiology | 3 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | |
| 0 | 16 | 0 | Microbiology | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | |
| 0 | 16 | 0 | Microbiology | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | |
| 1 | 19 | 1 | Public_Admin | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 0 | 18 | 1 | Accounting | 4 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | |
| 1 | 21 | 1 | Accounting | 3 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | |
| 0 | 21 | 1 | Accounting | 3 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | |

### 4.4 Application Algorithm

**Step1:** *Let n be the number of instances in the training data*

*For each of t iterations do*

*Randomly sample n instances (using deletion and replication)*

*Apply a learning technique to build a model from the sample*

*Store the model*

*Make prediction from the model from test set*

***End***

**Step2:** *Assign equal weight to all instances*

*For each of t iterations do*

*Apply a learning technique to build a model from the weighted instances*

*and store the resulting model*

*Down-weight each instance correctly classified by the model*

***End***

#### 4.4.1 Pseudo code/sequence of micro-operations/flowcharts

**Step 1-** ***Start***

**Step 2-***Take input which is given by User*

*In= {I1,……..,In}<<<<<<*

**Step 3-***Dataset preparation*

*Dn = { {I1,…In}D}*

**Step 4-***Dataset elaboration*

*DI ={S1,….Sn, C1,…..Cn, I1,…..In, a1,…..an}*

**Step 5-** *Processing*

*While( Dn!=0 )*

*{ If ( an==In)*

*Check Cn, Sn;*

*}*

**Step 6-** *Result Generation*

*R={ Sc, Sn , Cn};*

*Where,*

*In = Input given by users*

*Dn = Dataset*

*D = Database*

*DI = Dataset contents*

*Sc= Semester Score*

*a1,….an= grade*

*S1,….Sn= Course*

*C1,….Cn= Category*

### 4.4.2 System Flowchart

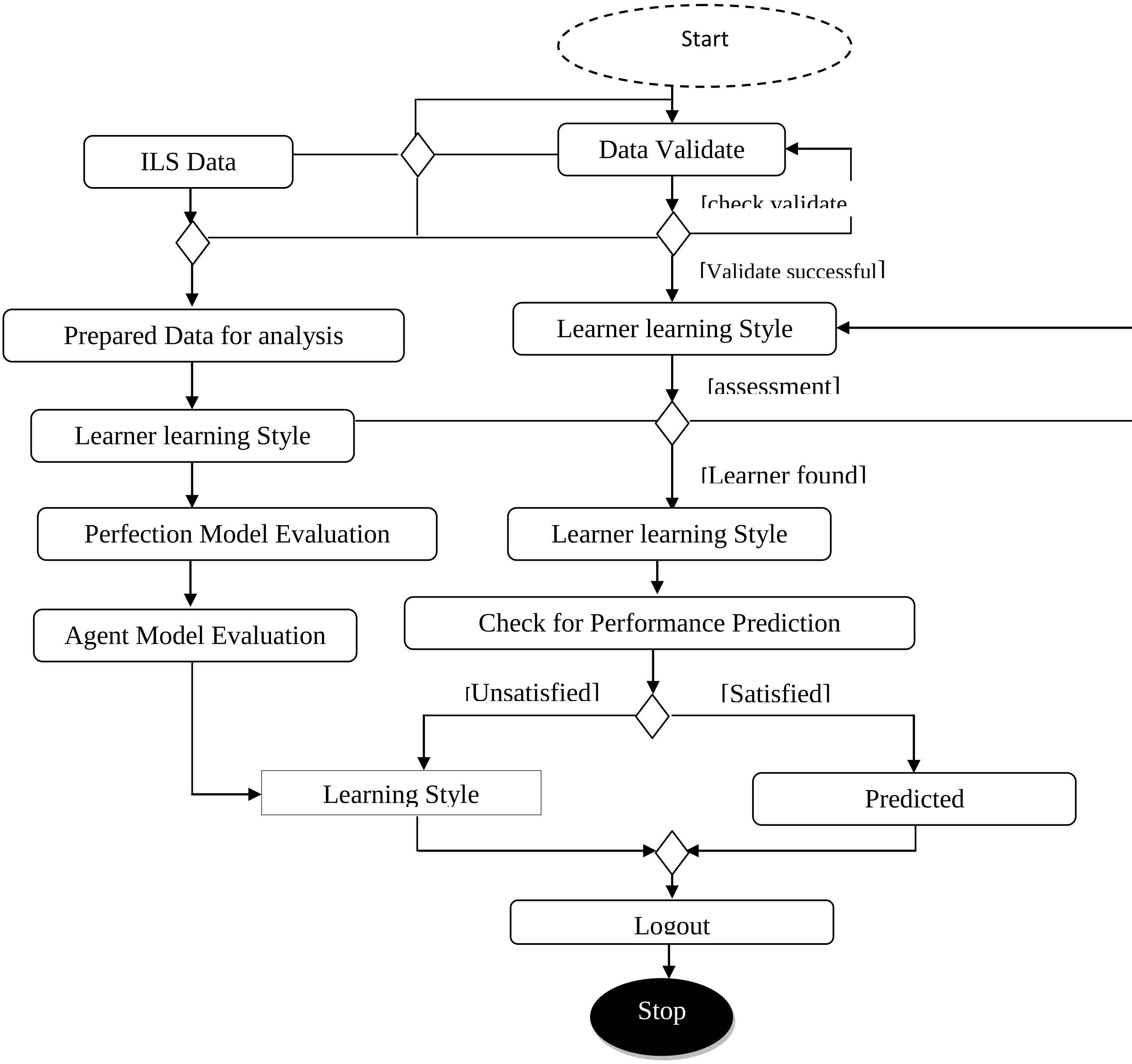


**Figure 4.3: System Flow chart**

## 4.5 The User Interface Design

The user interface design creates an application environment that makes the user's interaction with the system simple and efficient, as well as how the user conducts certain interactions and the interface design's usability.

The user interface design provides the application environment that makes the user's engagement with the system simple and efficient in achieving user goals, how the user conducts various tasks, and the usability of the human-computer interaction.

The user interface design in this system consists of nine different windows (or pages); these windows include:

### 4.5.1 Click Here to Login

This the first module that provide the link to click, where user can input his/her password for accessing the other module.

This module provides a link to admin input it user name and password to access the other modules where admin can now operate it for evaluating student attrition prediction concerning a specific task. It has all the various tasks for the user to use in accessing student attrition prediction.

### 4.5.2 Login Page

This page required the user to input his/her password for accessing the main menu module.

This module provides a link to other modules where users can input his/her authenication in other to access the student attrition prediction task. It has all the various tasks for the user to use in accessing student attrition prediction.

### 4.5.3 Main Menu Module

The main function of this module is that it contains both the main menu and sub-menu and it provides access to other modules to be operated by administrators. The first main menu here is the user home page interface showing the picture of this

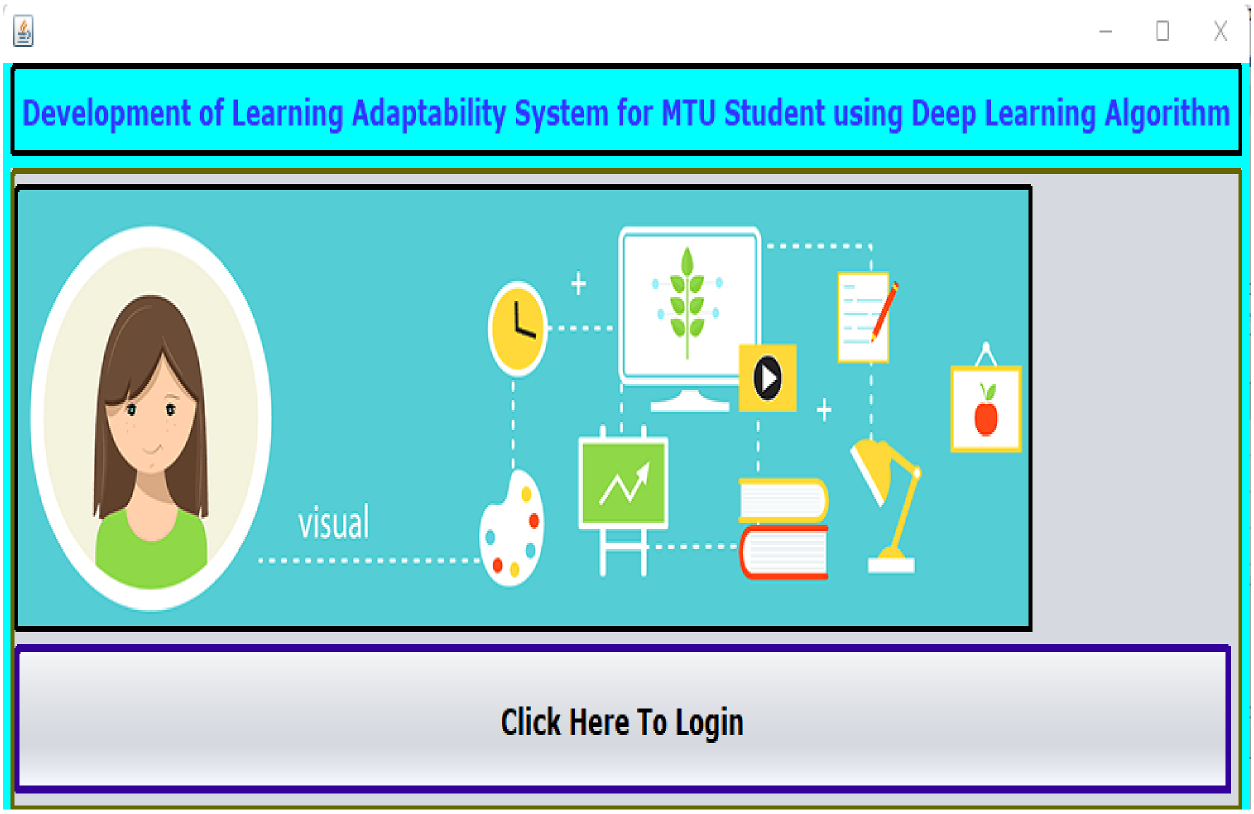


**Figure 4.4: Click Here to Login**

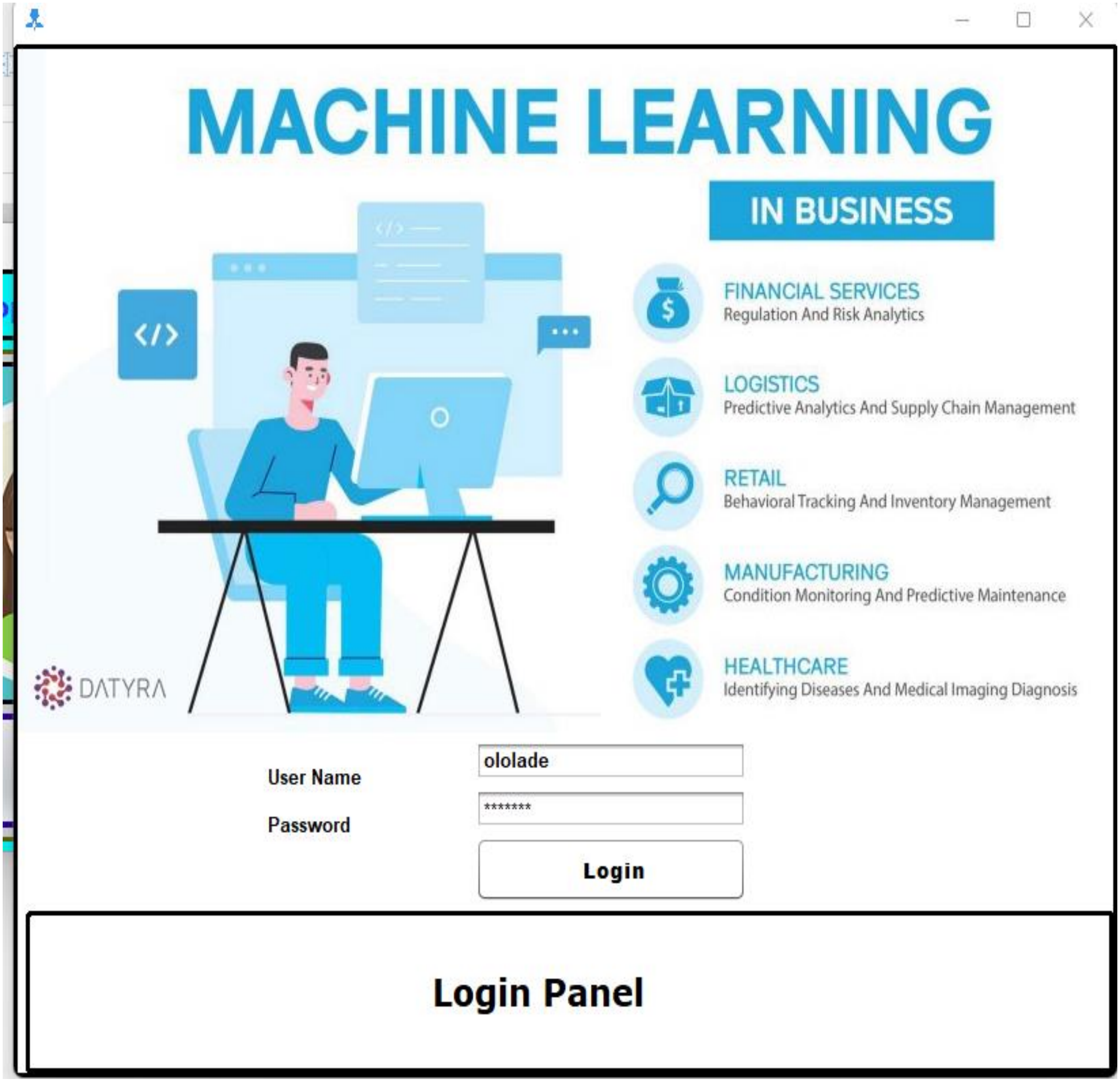


**Figure 4.5: Login Page**


**Figure 4.6: main menu Module**

This module provides a link to other modules where users can now operate it for evaluating student attrition prediction concerning a specific task. It has all the various tasks for the user to use in accessing student attrition prediction. It contains both the main menu and submenu, in this research work

### 4.5.4 View Structured Dataset Module

The function of the view structured dataset module has to do with the student data collected through the arched file from the MTU student and with their academic record. The total data collected was five hundred and sixity five samples (565) and this data was preprocessed before applying the classification model, the structured dataset is multiclass. Because it has multiple class values of identifying the student academic attrition prediction based on academic reports. The study analysis was achieved from this structure dataset. The data was preprocessed in an excel application package, notepad++, and converted to csv, arff (weka file format) before it was uploaded into the MyQSL database for further analysis. Below is the snapshot of the program interface module

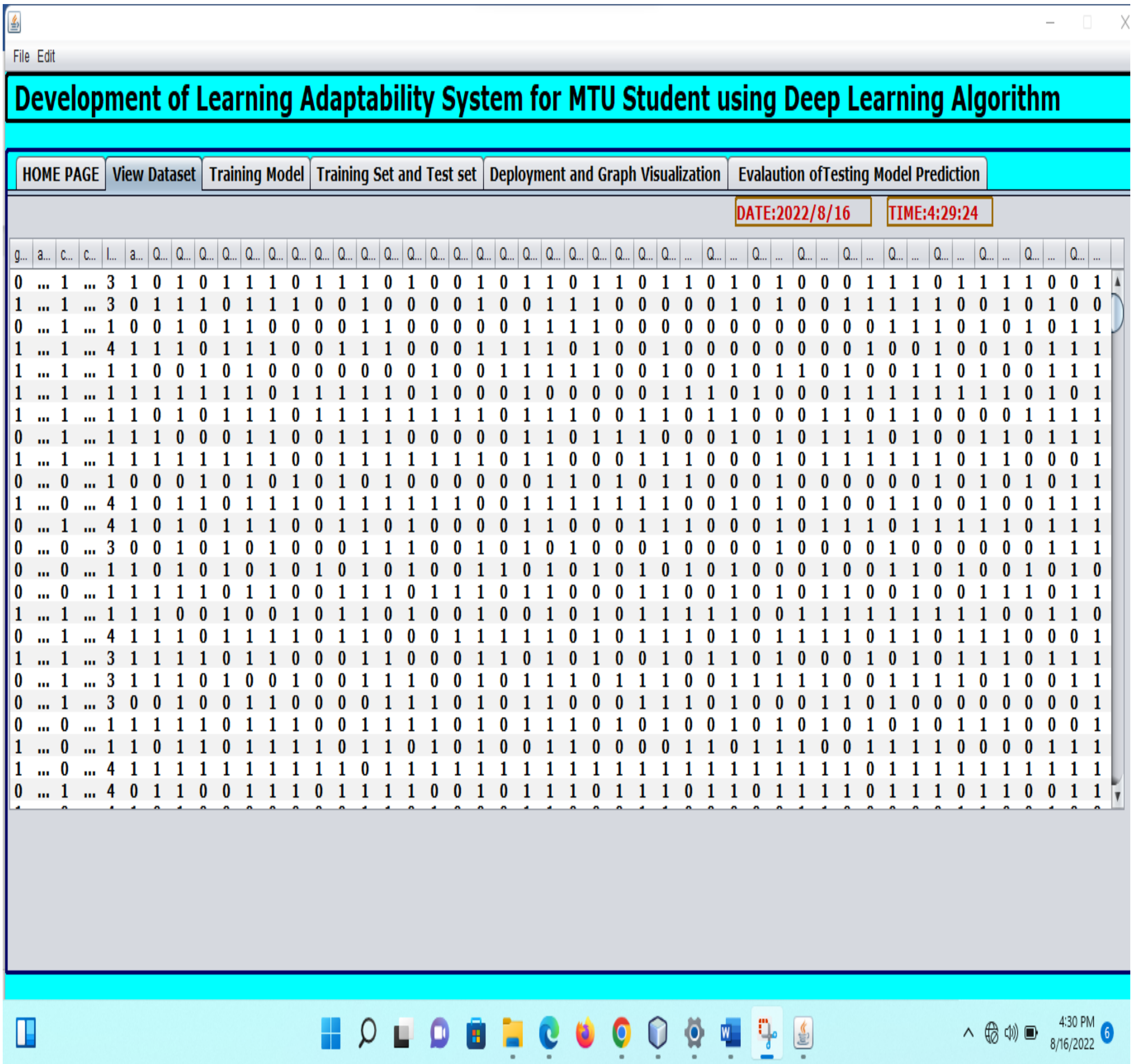


**Figure 4.7: View Structured Dataset**

This module used structured data set for predicting student attrition. The segmented into student academic results were used to form the basis of this analysis.

### 4.5.5 Model Building and Evaluation Interface for ANN classify

The model building program module used the element of the Weka machine learning library, and NetBeans IDE to implement the model for the full training set. The system used the pre-processed dataset of students, feature set extraction, and classification model, and this pre-processed data set collected via academic record was used to implement the model-building program module. The dataset has undergone model evaluation and 10-fold cross-validations, which mean 80% of the training set and 10% of the test set. The Training set is for model building and the test is for model evaluation. The model building was trained with a random forest classifier which has the weka library, for the implementation of model building for predicting student academic attrition with random forest, and the model calculate elapsed time by a java program in seconds and milliseconds. Below is the program module

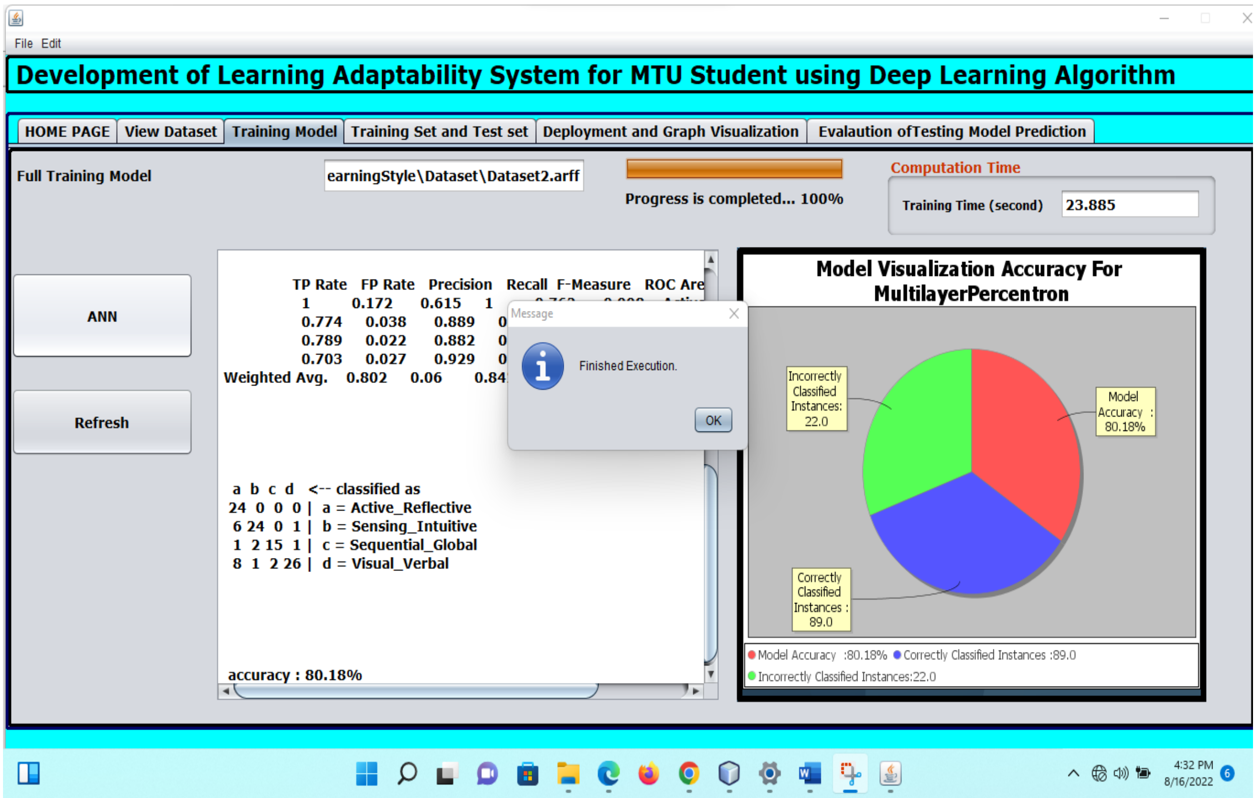


**Figure 4.8: Model Building and Evaluation Interface for ANN**

The system evaluates the model by using the prediction model with the processed training data, used the training dataset for predicting student attrition with actual student attrition, and evaluates the model by the Confusion Matrix and performance accuracy.

### 4.5.6 Model Building and Evaluation bar chat Interface for ANN Module

The program module was responsible for model evaluation which was based on their performance evaluation by a bar chart showing the following the class of degree setting such as sensing-intuitive, visual-verbal, active-reflective, and sequential-global, respectively for evaluating the learner prediction on metric evaluation model with each bar representing the model performance. The analysis was done with a classification model and the results were represented on the bar chart graph with a good performance. The high bar represents the learner with the highest grade, the low bar represents the learner with the lowest grade which needs to advise by the management and know to want to do to increase their chances of better performance and for the class of grade too. Below is the program graph module

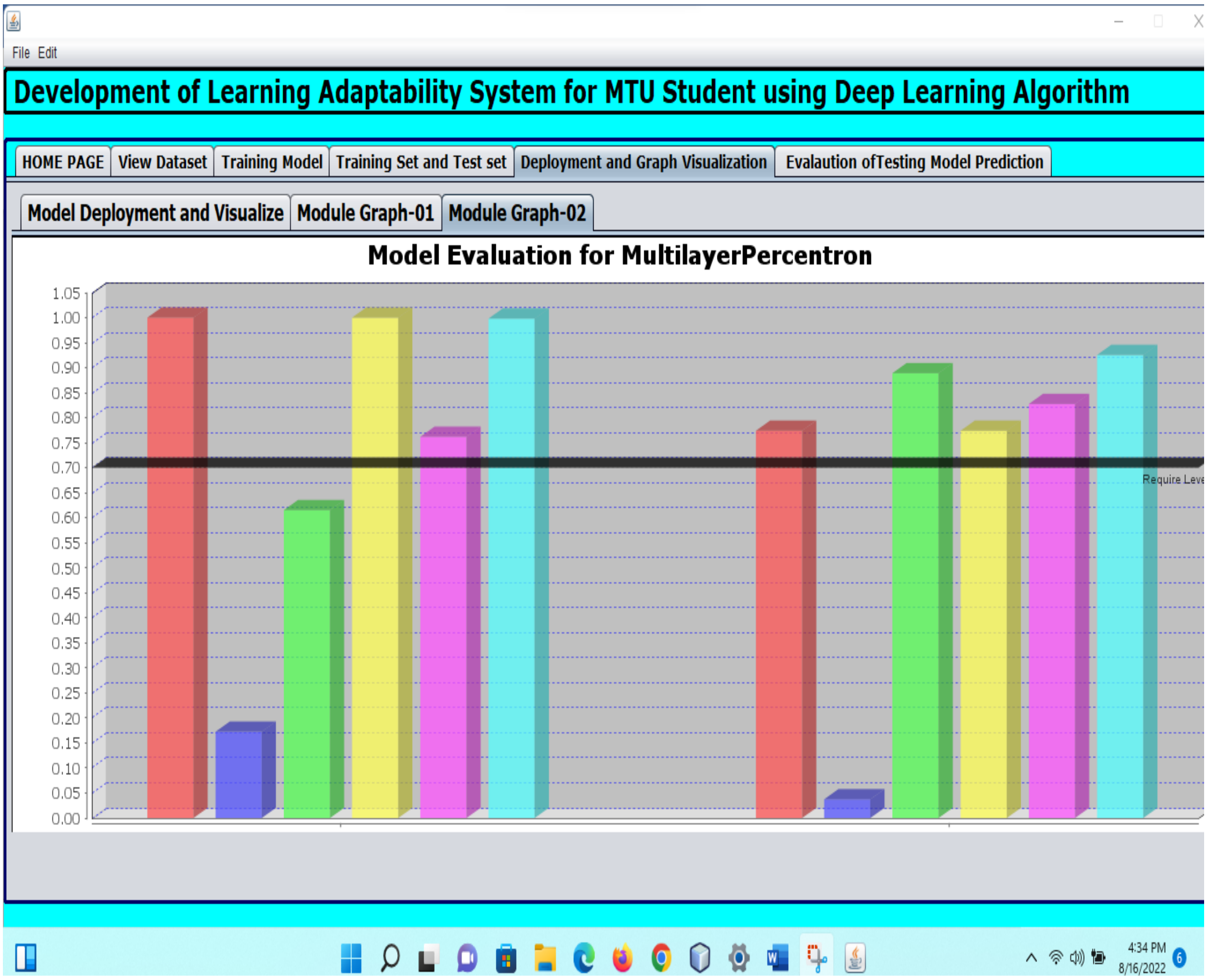


**Figure 4.9: Model Building and Evaluation bar chat Interface for ANN**

### 4.5.7 Model Building and Evaluation pie chart Interface for Random Forest Module

The program module was responsible for model evaluation which was based on their performance evaluation by a pie chart showing the following setting feature, the accuracy of Random Forest for the model evaluation is 84.68%. The analysis was done with a classification model and results were represented on the bar chart graph with a good performance. Below is the program graph module

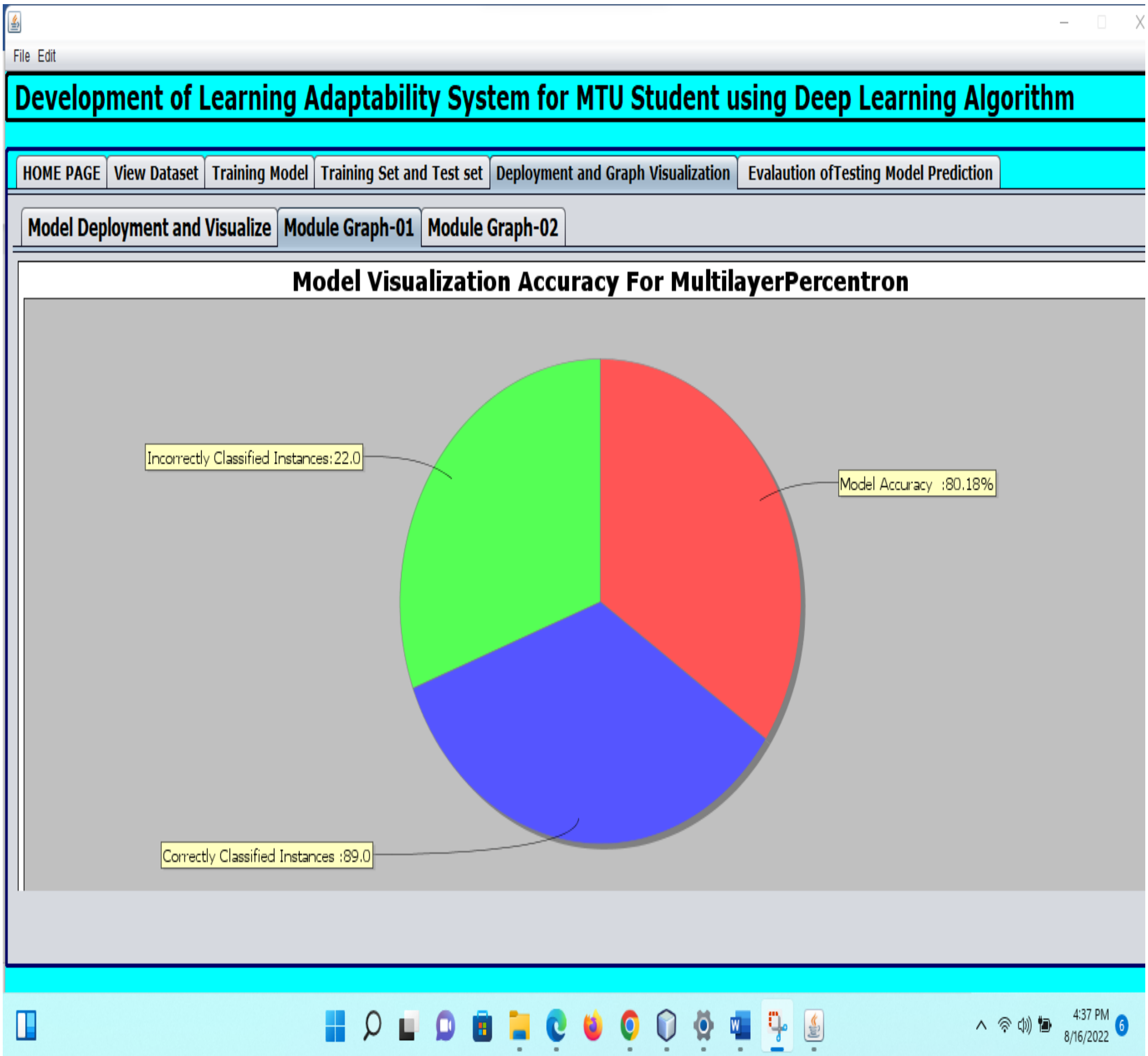


**Figure 4.10: Model Building and Evaluation pie chat Interface for ANN**

### 4.6 System Implementation

Based on this research work, we used Java programming language (NetBeans IDE) to implement the system, and that is the environment where the program code is written. And the functionalities of the system were written using traditional java classes and then these classes are converted into an agent-based behaviour. The implementation was done in Java programming language to take advantage of the existing library WEKA. WEKA (Waikato Environment for Knowledge Analysis) is an open-source toolkit, and it consists of a collection of machine learning algorithms for data mining tasks. The study also uses six algorithms in the system to evaluate the student attrition of the system.

**User Interface:** It is also responsible for student assessment data and their information such as feature/attributes variables, registration number, session, semester, and other types of data e.g. (academic-related factors).

**Model Full Training:** It is used for building the prediction model; this model is required to use the sample training data from the user interface agent. The data will be trained with a class label and store in a required format for the classifier to use for performing the optimization results. The process will be done with the number of iteration and display the result (Prediction Model) to the user interface.

**Model Evaluation:** This model is used to evaluate student attrition prediction; it receives the evaluation request from stored data with the required number of a sample set: it contains the prediction model, test data set and the actual students' assessment to evaluate the model and display the evaluation results to the user interface.

**Performance Prediction:** This model required the student level and predict their attrition as well as to receive the prediction request from User Interface with the required test set data: prediction model and students' data to be predicted are stored in a required file format to be ready for prediction request from user's interaction. Students used their level of entry to predict their attrition, this will be based on the selected student with the predicted attrition results

### 4.6.1 Proposed System Requirements

The proposed system requirements are based on after processing of collected data which is now being ready for training and testing. This is where the performance of the algorithm, quality of data, and are required where the output of data pre-processed are all appears to be out. From the data set collected 90 percent of the data is utilized for training and 10 percent of the data is reserved for testing. Training as discussed before is the process of making the machine learn and giving it the capability to make further predictions based on the training it took. Whereas testing means already having a predefined data set with output also previously labelled and the model is tested whether it is working properly or not and is giving the right prediction or not. If the maximum numbers of predictions are right, then the model will have a good accuracy percentage and is reliable to continue with otherwise better to change the model.

Hardware Requirements

The following hardware components are needed

i. Personal computer (PC) – a desktop or laptop

ii. Printer – a desk jet or inkjet

iii. Scanner – Preferably colour scanner pictures.

The personal computer should have a minimum of

i. Pentium 4 Processor

ii. 8GB RAM

iii. 500 GB Hard disks

Software Requirements

i. Installation of Java jdk into your system

ii. Java run time Environment (JRE)

iii. NetBeans IDE version 7.3.1 or latest

iv. Weka Run-Time Environment (WRTE)

v. Weka Tool version 3.8.1 (Machine Learning Techniques)

vi. Notepads++

### 4.6.2 Program Development

The main processes involved in this research work are feature extraction, classification, and prediction. For this purpose, the study uses java programming to implement a machine learning model.

**Java**

For performing data pre-processing and feature extraction, Java Development Kit (JDK) and software development kit (SDK) are used. It contains a Java compiler, a full copy of the Java Runtime Environment (JRE), and many other important development tools. MySQL JDBC Driver and edu.mit.jwi_2.1.4 are the two main libraries used for pre-processing data

**Choice of Programming Environment**

Net Beans IDE is used to develop machine learning applications using a java programming language quickly and easily. It provides support for Java Development Kit 7. Here Net Beans Integrated Development Environment runs on the Java SE. Development Kit (JDK) which consists of the Java Runtime Environment plus developer tools for compiling, debugging, and running the applications written in the Java language as well as WEKA library was used as a choice of the programming environment.

**Data Formatting:** Convert the students' data in the Excel file to the ARFF file (Attribute Relation File Format).

**Data Partitioning**: The data will be divided into training and testing data. The training data is applied to build the model while the testing data is used to verify the model.

**Performance Prediction Model Building:** Build the performance prediction model from Training Data using data mining technique. The study used the six-classification task, to build the performance model and for performance optimization.

**Performance Prediction Model Evaluation:** Evaluate the prediction model by Test Data using the confusion matrix and calculate the prediction accuracy and store the evaluated Model.

**Students' Performance Prediction:** Predict the students' performance and optimize the predicted students' attrition and store students' assessment and students' activities/data to be ready for attrition prediction requests.

**Students' Attrition Prediction Model Building and Evaluation**:

i. **Build the Model**: This is used to the training data description, these data are file name; relation name, attributes number, students' number, and attributes list with its data type. The study chooses a model with 10 iterations and clicks on the classification model. A composite model (6 classifiers) is built, and each classifier has a weight that indicates its accuracy for performance optimization.

ii. **Evaluate the Model:** The study selects the pre-processed Test Data and click on Evaluate the Prediction Model

### 4.6.3 System Testing

Before a system is put into operation, its components programs must be tested to make sure it works both individually and as a unit. Testing whether unit testing (individual testing) or individual testing, removes bugs from individual programs and system applications. The testing of this system is done with training data set and test data set. The system may have a hundred programs and a comprehensive database, all must be tested together to ensure harmony of operation. The purpose of system testing is to validate all software, input/output, databases, and procedures, and so on as the case may be.

## Test Plan

After completion of the detailed design, the design team will develop a plan for testing the software or database component to be developed from the design specifications. Data sets must be generated as part of the test plan that will effectively test all functions of the software and its data outputs as defined in the specifications. Matrices of the test data will be developed and documented that define the known values of all input data elements and the expected output values for each data element. The matrices will also contain cross-references to the design specifications for each function to be tested. If new or unique data files and data structures are required for the testing, two test data sets must be developed: one for use by the software developers for testing of their software and one for the formal testing of the software under controlled conditions. The plan must cover all phases of the test to be performed including modular, integration, system, acceptance, and regression/classification testing. The test plan will also be developed to assure the following types of testing:

**Functional Testing**: Testing to assure that the functional requirements of the design are met.

**Performance Testing**: Testing to assure that response times, run times, and other phases of execution are within acceptable limits and time frames

## Test Data

Tests are conducted at all levels of the system development process by assigned review teams using approved test data plans and validated test data sets. Unit, modular, integration, system, acceptance, and classification data mining tests are conducted on all modules of the system. Each of these tests is discussed in a subsection of this plan. Testing is done at the times of system development and system implementation, and each time a change is subsequently made in the system.

## 4.7 System Specifications

The system specification for this research study is based on student prediction using machine learning techniques which used a machine learning model for developing this study and such model was Waikato Environment for Knowledge Analysis (WEKA). WEKA is an open-source tool written in Java that is widely used by data miners. WEKA implements most of the machine learning algorithms and visualizes its results as well. NetBeans IDE, MySQL Database. Based on this concept, the KDD analysis design modelling comes in place, specification is needed:

i. Installation of Java jdk into your system
ii. Java run time Environment (JRE)
iii. Netbeans IDE version 7.3.1 or latest
iv. Weka Run-Time Environment (WRTE)
v. Weka Tool version 3.8.1 (Machine Learning Techniques)
vi. Notepads++

### 4.7.1 Database Development Tool

WEKA provides access to SQL databases using Java Database Connectivity and can process the result returned by a database query. The WEKA supports several standard data mining tasks, more specifically, data pre-processing, clustering, classification, regression, visualization, and feature selection. All WEKA's techniques are predicated on the assumption that the data is available as a single flat file or relation, where each data point is described by a fixed number of attributes (normally, numeric, or nominal attributes, but some other attribute types are also supported). Netbeans, this is an integrated development environment (IDE) for Java. NetBeans allows applications to be developed from a set of modular software components called modules. In addition to Java development, it has extensions for other languages like PHP, C, C++, HTML5, and JavaScript which is suitable for this research work.

### 4.7.2 Database Design and Structured

Database names were created and organized into physical files optimized for speed. The databases were structured into tables, views, rows, size, and columns. Rules were set up to govern the relationships between different data fields. These include:

i. Student Dataset Table
ii. Student Learner Table

### 4.7.3 Contingency Specification

The confusion matrix or contingency table is a visualization tool commonly used to present the performances of classifiers in classification tasks. The study used it to show the relationships between real class attributes and that of predicted classes. The level of effectiveness of the classification model is calculated with the number of correct and incorrect classifications in each possible value of the variables being classified in the confusion matrix. For instance, given two classes the contingency or confusion matrix can be given as in Table 4.2 below:

**Table 4.2: Contingency Table**

| Contingency | Predicted Class | | |
|---|---|---|---|
| Actual class | Class | Class A | Class B |
| | Class A | **True Positive (TP)** | *False Negative (FN)* |
| | Class B | *False Positive (FP)* | **True Negative (TN)** |

Table 4.2 describe the true positives (TP) mean the correct classifications of the positive class A; true negatives (TN) are the correct classifications of the negative class B; false positives (FP) represent the incorrect classification of the negative class A into the positive class A, and false negatives (FN) are the incorrect classification of the positive Class B into the negative class B. Below illustrate a mathematics equation for student attrition prediction:

i. The predictive **accuracy** of the classifier measures the proportion of correctly classified instances = TP+TN/TP+FP +TN +FN
ii. **True Positive Rate** (**TPR or Recall or Sensitivity**): measures the percent of actual positive class A that are correctly classified = TP/(TP+FN)
iii. **True Negative Rate (TNR or Specificity):** measures the percent of actual negative class B that are correctly classified = TN/(TN+FP)
iv. **Positive Predictive Value (PPV):** often called Precision, it is the percentage of the class predicted to be positive that were correct = TP/(TP+FP)
v. **False Negative Rate (FNR):** The percentage of positive examples that were incorrectly classified = FN/(TP+FN) = 1−TPR
vi. **False Positive Rate (FPR):** The percentage of negative examples that were incorrectly classified = FP/(TN+FP) = 1−TNR

The machine learning algorithms were considered because of accuracy in classification, Kappa statistic, and mean absolute error need to be considered and compared. Initially, the classifiers are considered for evaluating the prediction results of sample data set instances, in which the results were observed and tabulated. Based on the results; an inference on rejecting

the classifiers are reached. Kappa statistic is a measure to show the agreement of prediction with the true results. Numerical implications of Kappa statistic are to be very high which shows the coincidence or absorption of attribute values in predicting the results. The Kappa statistic varies from 0 to 1, were,

i. 0 = agreement equivalent to chance.
ii. 0– 0.20 = slight agreement.
iii. 0.21 – 0.40 = fair agreement.
iv. 0.41 – 0.60 = moderate agreement.
v. 0.61 – 0.80 = substantial agreement.
vi. 0.81 – 0.99 = near perfect agreement.
vii. = perfect agreement.

Here are some other factors in classifier output

**TP Rate:** rate of true positives (instances correctly classified as a given class)

**FP Rate:** rate of false positives (instances falsely classified as a given class)

Precision: proportion of instances that are true of a class divided by the total instances classified as that class

**Recall:** proportion of instances classified as a given class divided by the actual total in that class (equivalent to TP rate)

**F-Measure:** A combined measure for precision and recall calculated as 2 * Precision * Recall / *(Precision + Recall)

#### 4.7.4 Program Screenshot/Interface Specification

The outcome of the proposed system result is based on the student attrition prediction using machine learning techniques which indicate the detailed analysis used to build the system and each stage of this system performs are specify in program module specification task which leads to the successful development of the system that yields the promising results. The program module for the student attrition prediction using data mining is listed below:

### 4.8 Performance Evaluation

**Table 4.3: Model Evaluation Performance Results**

| Classifier | Model Evaluation on Test set (111 instances) with 80% and 20% of Resume Technique | | | | |
|---|---|---|---|---|---|
| | **Correctly Classified Instances Student** | **Incorrectly Classified Instances Student** | **Accuracy** | **Kappa statistic** | **Mean absolute error** |
| ANN | 80.1802 % | 19.8198 % | 80.18% | 0.7342 | 0.095 |

Model Information

=================

| | | |
|---|---|---|
| Correctly Classified Instances | 89 | 80.1802 % |
| Incorrectly Classified Instances | 22 | 19.8198 % |
| Kappa statistic | 0.7342 | |
| K&B Relative Info Score | 8603.5051 % | |
| K&B Information Score | 168.5353 bits | 1.5183 bits/instance |
| Class complexity \| order 0 | 217.1069 bits | 1.9559 bits/instance |
| Class complexity \| scheme | 123.255 bits | 1.1104 bits/instance |
| Complexity improvement (Sf) | 93.8519 bits | 0.8455 bits/instance |
| Mean absolute error | 0.095 | |
| Root mean squared error | 0.2624 | |
| Relative absolute error | 25.8454 % | |
| Root relative squared error | 61.2149 % | |
| Total Number of Instances | 111 | |

| | TP Rate | FP Rate | Precision | Recall | F-Measure | ROC Area | Class |
|---|---|---|---|---|---|---|---|
| | 1 | 0.172 | 0.615 | 1 | 0.762 | 0.998 | Active_Reflective |
| | 0.774 | 0.038 | 0.889 | 0.774 | 0.828 | 0.925 | Sensing_Intuitive |
| | 0.789 | 0.022 | 0.882 | 0.789 | 0.833 | 0.919 | Sequential_Global |
| | 0.703 | 0.027 | 0.929 | 0.703 | 0.8 | 0.951 | Visual_Verbal |
| Weighted Avg. | 0.802 | 0.06 | 0.842 | 0.802 | 0.805 | 0.949 | |

a b c d <-- classified as

**24** 0 0 0 | a = Active_Reflective

6 **24** 0 1 | b = Sensing_Intuitive

1 2 **15** 1 | c = Sequential_Global

1 2 **26** | d = Visual_Verbal

### 4.8.1 Limitations of the System

The study is limited to a specific task, is used the sample of training dataset collected for this research study which was collected through academic assessment results which form the basis of this thesis. And due to the little time contain our work is limited to a structured dataset only

### 4.8.2 System Security

The developed system is protected with a level of operation, and it required the admin to input his username and password that was registered before he/she can gain access to application packages else it will deny you access. Like for those who are using the software, they were expected to be registered tools for them to enjoy the service

**Password Protection**

The password protection was done to secure unauthorized user hacking into the system without the notice of administration. For this research work, it is only the administrator that will grant access to the user before he/she is permitted to use the services or application

**Authentication**

The authentication was done for both admin and user. It required both username and password created during the execution program development phase. The username and password are stored in the back end (Database) and the front end expect a user to input his/her username and password for granting access to the application

### 4.9 Training

The proposed new system recommended that the user of the new system is being trained on its functionality and parameters needed to enable them to make maximum usage of the new system.

### 4.10 Documentation

The documentation in the dissertation was mainly focused on how the application will be used installed. To install it on the system to run from the hard disk, follow the procedure below.

i. Install Java jdk version 1.7.0 on the computer
ii. Install Weka Machine learning version 3.8.0
iii. Install Jade Agent platform
iv. Install Java Virtual Machine
v. Install Netbeans IDE version 7.3.0
vi. Install notepad++
vii. Install MySQL Server (Wamp)
viii. Insert the CD-ROM plate into your system
ix. Click Drive:
x. Select the folder “AttritionPrediction”
xi. Pate it inside Netbeans Project you have installed

xii. Launch the Netbeans project to have access to the application

xiii. Inside Attrition upload your database to MySQL server:

xiv. Right-click on the application you just uploaded int Netbeans Project’”’

xv. Click Run

xvi. Enter the username and password and click login

xvii. Select options from the menu for the operation of the system

**4.11 Changeover Procedures**

The proposed were implemented after it has been tested and this is known as system conversion. It is a process of changing over from the old system to a new secured system.  It can be performed in any of the following ways:

i. Pilot Conversion

ii. Phased Conversion

iii. Parallel Conversion

iv. Direct Conversion

**Pilot Conversion**

This approach involves the trial of the new system in only one part of the organization. Once the system is working out smoothly in that part, the focus is then shifted to other parts of the organization.

**Parallel Conversion**

In this approach, old and new systems are operated side by side until the new one has shown that it is reliable. This approach is low risk. If the new system fails, the organization can just switch to the old system to keep going. This method, however, is expensive as it keeps people and equipment active to manage the two systems.

**Phased Conversion**

This approach is like the parallel approach except that initially, only a portion of the current data is run in parallel on the new system, for instance, that of student performance prediction only. In each case, the old system runs in parallel for one processing cycle only. Thus, the old system is phased out as the new system builds up.

**Direct conversion**

This involves taking the old system with a single model and putting the new system on a hybrid model for performance prediction. However, if there is a problem with the new system there isn't anything to fall back on.

### 4.11.1 Recommended Procedure

i. Parallel changeover is recommended for this system in which both the old and new systems are operated concurrently for some time until the new system is certified functional. This is to enable the management to fall back to the old system should the new system pose some challenges in its usage. The management should also take full advantage of this research by using the program in identifying those students with the likelihood of failure in school, putting measures in place to ensure those identified students are properly guided and counselled, thereby increasing their likelihood of success.

ii. The management should make available wireless networks in the school to enable all the students to access the internet to consult educational materials that will further enhance the knowledge imparted to them by the lecturers

iii. The management should provide a conducive learning environment for the student to read as this could facilitate the rate at which they assimilate what they are thought in the school

## CHAPTER FIVE

## CONCLUSION, RECOMMENDATION AND FUTURE WORK

### 5.1 CONCLUSION

This project (development of learning adaptability system for MTU student using a deep learning algorithm) is concerned with the use of data mining algorithm for the extraction of features from external environment and classification in order decipher whether a student learning style. Other systems have been built already, but some of these existing systems are expert systems, and are often complex and hard to relate with. Furthermore, they are not so accurate in their prediction and hence are not so reliable.

In this study, the strength of artificial neural network (ANN) was used in predicting student learning style to unstructured the dataset that was developed with java programming language as well as machine learning model namely (WEKA machine learning classification analysis) by the virtue of its performance in predicting student learning style and the result shows that it is a good machine learning environment for performance evaluation of data mining technique. The analysis of ANN forms the concept of the trained model to learn from the features and predict the result. All algorithms achieved a good accuracy rate model on the test set.

### 5.2 RECOMMENDATION

This project was designed to predict student learning style of four-dimension class of learning objects using artificial neural network, which achieved a good result respectively of our data for test set. ANN has been a fast classifier and with the simplicity machine learning model to gives a better result. Hence this system is highly recommended to everyone, especially the education sector, as a tool that can be used to make prediction of student learning style easier and accurate.

### 5.3 FUTURE WORK

Different algorithm may be trained to see which one yield a better result also different set of features may be tried to see if there exist a set of features which give the same result. Feature extraction should be done in some care to train these learners with the most relevant features. The project could be narrow to classify any number of student learning style predictions which since this project predicts four-dimension objects.

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