Predictive Analytics for Determining Learning Outcomes in Intelligent Tutoring Systems

A Thesis Report

submitted in partial fulfillment of the requirements

for the award of degree

of

Master of Engineering

in

Computer Science and Engineering

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July 2016

CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, "***Predictive Analytics for Determining Learning Outcomes in Intelligent Tutoring Systems***", in partial fulfillment of the requirements for the award of degree of Master of Engineering in ***Computer Science and Engineering*** submitted in Computer Science and Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of ***Ms. Harkiran Kaur*** and refers other researcher's work which are duly listed in the reference section.

The matter presented in the thesis has not been submitted for award of any other degree of this or any other University.

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This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

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ACKNOWLEDGEMENT

I would like to express my most sincere appreciation and deep sense of gratitude and indebtedness to my guide **Ms. Harkiran Kaur,** Lecturer, Computer Science and Engineering Department, Thapar University, Patiala for providing me continuous guidance throughout the research. It has been possible to proceed in the correct direction and successfully complete the thesis with her valuable suggestions. I would like to thank her for encouraging my research and for being actively involved in my work.

I am also thankful to Dr. Maninder Singh, Head of Department, CSED and Dr. Ashutosh Mishra, P.G. Coordinator, for the motivation and inspiration that triggered me for the thesis work.

I am also very thankful to the entire faculty and staff members for the direct-indirect help, cooperation and support.

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ABSTRACT

Educational structure in general and the learning process specifically are heading for a rapid transformation. Computers and computer networks are becoming major sources of information for the present and future generations. The emergence of computers and technology has opened up new avenues in the field of education. One of the major advancement is the development of Intelligent Tutoring Systems. This work introduces Intelligent Tutoring Systems along with their typical architecture, developmental history, past and presents systems and proposes a new concept of user profiling for better adaptivity in Intelligent Tutoring Systems. Cognitive factors such as concentration level, motivation level, mental speed, initial knowledge level and importance of task to the learner have been considered to have a huge impact on learning outcomes. Based on the values of these parameters, Naïve Bayes classifier has been used to classify the learner into three classes Beginner, Medium and Advanced. This classification is beneficial to determine the initial learning scenario and to provide personalization to each learner as every learner has its own cognitive skills and learning preferences. The amalgamation of emotions, human psychology, cognitive abilities, meta-cognitive abilities and the learning abilities with the ITS has introduced a new generation of ITS that is "Affective Tutoring Systems".

Keywords: Intelligent Tutoring Systems, Naïve Bayes Classifier, User Profiling, Cognitive Skills, Student Modeling, Personalization.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

ITS	Intelligent Tutoring Systems
AI	Artificial Intelligence
ATS	Affective Tutoring Systems
EMG	Electromyogram
EEG	Electroencephalography
EDA	Electro Dermal Activity
SC	Skin Conductance
ECG	Electrocardiogram
BVP	Blood Volume Pulse
LSA	Latent Semantic Analysis

CHAPTER 1

INTRODUCTION

1.1 Introduction to Intelligent Tutoring Systems

An Intelligent Tutoring System is a technology based program which simulates a human tutor's behavior and provides personalization in the learning process based on his learning environment preferences and the performance of the learner [23]**.** It is able to assist students studying a variety of subjects by posing questions, analyzing responses, and generating customized instructions and feedback. A very important factor with which Intelligent Tutoring System is differentiated from other types of computer-aided instruction is that, it can interpret student responses and learn as it functions eventually. The system builds a profile for each student and estimates the student's degree of knowledge over the subject. The system then alters its tutoring behavior in real time, following differences in individual students' preferences for more effective interaction with all students. The intelligent tutor not only detects that a response is incorrect but also identifies where in that response the student has gone wrong. To accomplish this, student's responses are monitored through a number of intermediate steps or in other words, student's performance is analyzed continuously so as to attain an effective progress.

1.2 Architecture of an ITS

The architectural components of an ITS are:

I. **Expert module:** The expert module in ITS stores the domain knowledge that the system desires the student to learn. It consists of various concepts, facts, rules and problem solving functionalities in context of the domain knowledge. It is considered as a standard medium for evaluating the performance of the student and diagnosing his errors. Different models use different methodologies to store the domain knowledge, some of which are explained below [30].

   i. **Scripts**: Scripts are a method of knowledge representation which provides facts, and it emphasize upon causality. It is a structure that stores prototypes of possible sequence of events. It consists of 'Nodes'

that correspond to processes and events and 'Links' between those nodes convey relations such as 'X causes Y' [3].

ii. **Rule-based representation:** IF-THEN rules or production rules are used in most areas of Artificial Intelligence (AI) for representation of knowledge. Further in ITS also, production rules are used in several systems for domain knowledge representation. Rule-based systems are flexible in nature. Rules can be added or deleted without affecting other rules as each rule is independent of the other [41].

iii. **Semantic Network:** Semantic Network is a graph based structure denoting associations between elements in a domain. The two fundamental components of a semantic net are 'nodes' and 'links'. Nodes are used to signify domain elements and links represent relations between elements. Reasoning based on semantic net is nearly straight forward because associations can be made simply by tracing the linkages in the systems. Semantic network has been used in many ITSs, for the purpose of knowledge representation [43].

iv. **Procedural network:** A procedural network for a skill is a decomposition of that skill into sub procedures, which are linked together in a lattice of sub goals. The links in a procedural network represent the procedure-calling relation down to a set of primitive actions. A procedural network is executable and can thus be run on a set of problems to model the skill that it represents. A diagnostic modeling scheme based on a procedural network contains all the necessary sub skills for the global skill. It uses the deep-structure model to identify the student's incorrect behavior in solving a problem [51].

v. **Generic graph:** The nodes of the generic graph represent the facts, rules or procedures which describe some of the expert knowledge, that is, a skill, sub skill or a concept. These links could be of types: analogies, generalizations and specializations [4].

vi. **Frame-based representation:** Frame is a data structure used to represent some prototypical situation or entity. More specifically, a frame is a cognitive structure which is used to assemble information making an entity. A frame is implemented as a collection of slots. Slots

are the frame components used to store variables which characterize the frame [53].

II. **Student module**: The student module in ITS represents the learner's recent knowledge state. This information helps the tutor to adopt the instructional strategy according to his performance, abilities and needs. The tutor accordingly chooses an appropriate method of presentation of the subject and decides the level of difficulty for the next problem to be posed. The functions of the student module can be divided into six categories [17]:

   i. Corrective: This function removes the errors in the conceptual and fundamental knowledge of the learner.
   ii. Elaborative: This function helps in enhancing the knowledge of the learner related to a specific concept. Also, this function removes the incompleteness of information (if any) in the student's mind.
   iii. Strategic: It helps in initiating and improving the tutorial strategy if required.
   iv. Diagnostic: This function helps in diagnosing the inaccuracies with-in the knowledge domain of the student.
   v. Predictive: Predictive function helps in determining the possible responses of a student to the actions offered by tutorial module.
   vi. Evaluative: The evaluative function is used to assess the student's performance.

III. **Tutorial module**: The tutorial module also known as the pedagogical module contains instructional strategies such as selecting a suitable presentation method which is effective as well as indulging for the learner, determining what next to teach or present and when to suspend the instructional process. The instructional strategies are decided based on the analyzed report provided by the diagnostic module and student module. It tracks the student's progress and analyses its strengths and weaknesses and thus progresses the learning scenario. The most important part of the tutoring module is assessment .Better the assessment, better the tutoring module. Tutoring module is closely connected with the expert module. The tutoring module continuously assesses the student and interacts with the expert module to decide the next act to be performed. Tutoring module then takes the decision based on various characteristics such as teaching history, student's response to several

presentation ways, learning habits and styles preferred. Tutoring systems incorporate micro-level strategies for tutoring and effective instructional strategies [30].

IV. **User-Interface module**: The User-Interface module provides a visual medium of interaction between the student and the system. This module presents the knowledge to the learner in textual form as well as in graphics format and is also responsible for acceptance of student input.

A functional model of an ITS is given in Figure 1.1:

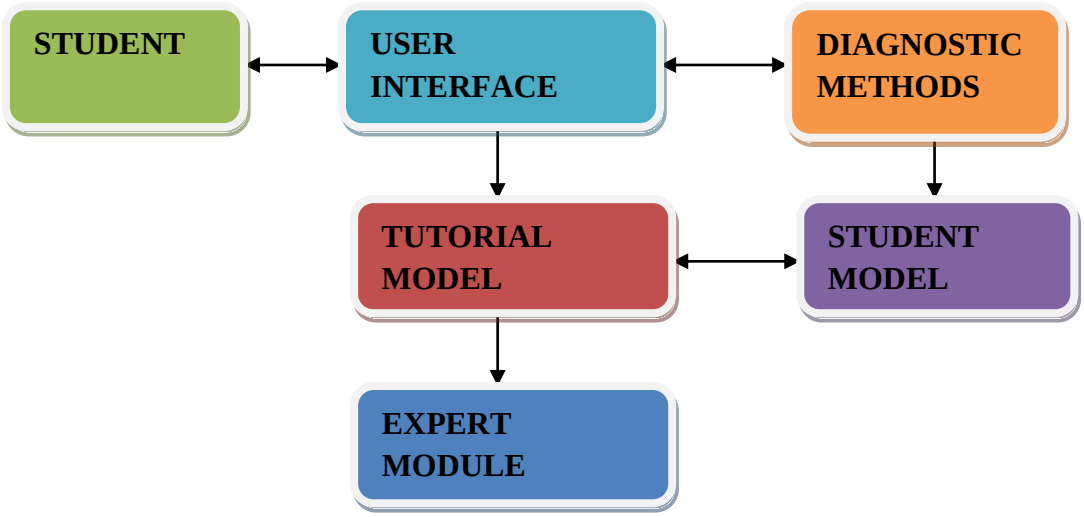

Figure 1.1: **Architecture of ITS**

1.3 Features of ITS

The major characteristic features of an ITS are as follows:

I. **Generative**: ITS generates appropriate problems, hints and feedback whenever required. Depending upon the learner's performance ITS decides the difficulty of the next question or whether or not a concept needs to be tutored before continuing further teaching [11].

II. **Self-Improving**: The most interesting characteristic of an ITS is its adaptivity and that it is self- Improving. It monitors, evaluates and improves its own teaching as a result of experience as it incorporates basic fundamentals of machine learning [6].

III. **Cognitive Modeling**: This feature enables the user to assess the learner's current psychological state along with his knowledge level and then deciding the instructional strategies and the tutoring process accordingly [12].

An example of working of modules is shown in Figure 1.2.

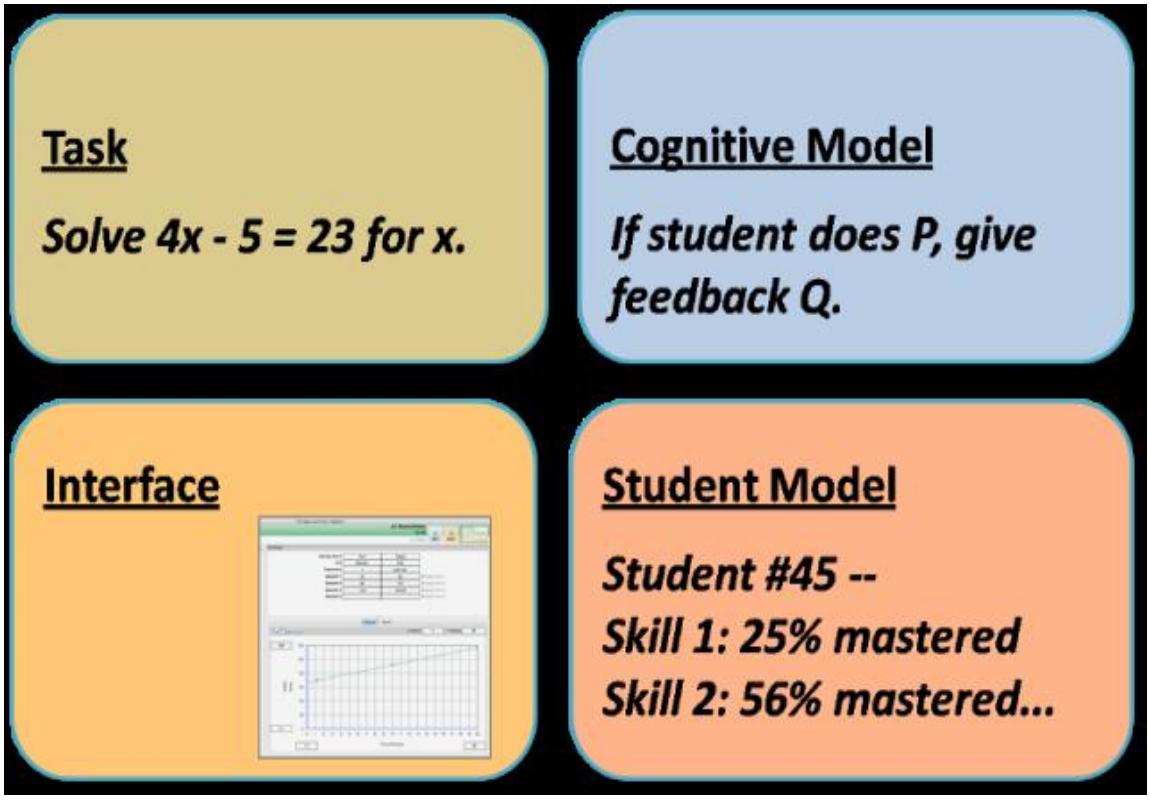

Figure 1.2: Pictorial depiction of modules of an ITS

1.4 Drivers of an ITS

The main drivers in an ITS includes [23]:

I. **Artificial Intelligence:** Artificial intelligence serves major two purposes: One is to use the power of computers and technology to simulate human thinking and other is to determine how mind thinks and operates. In ITS, AI operates both ways. The artificial intelligence techniques play a major task in enhancing the characteristic features of the ITS. AI enables the management of domain knowledge and also it is the vital cause due to which ITS is supposed to be self-improving and generative.

II. **Cognitive Science**: Cognitive Science is an interdisciplinary field including various disciplines such as mind and intelligence, psychology, anthropology, physiology and neuroscience as shown in Figure 1.3. Study of cognitive science leads to a better understanding of how people think and perceive,

solve problems and learn. Cognitive science is necessary to be incorporated in ITS so as to offer adaptivity and personalization as each student has different level of cognitive skills. Current Intelligent Tutoring Systems can be called as the true combination of Computer Science, Cognitive Science, and Educational Research. Various focus areas have been offered in the development of systems across varying time periods highlighting areas of research which are continuously being addressed by scholars and researchers.

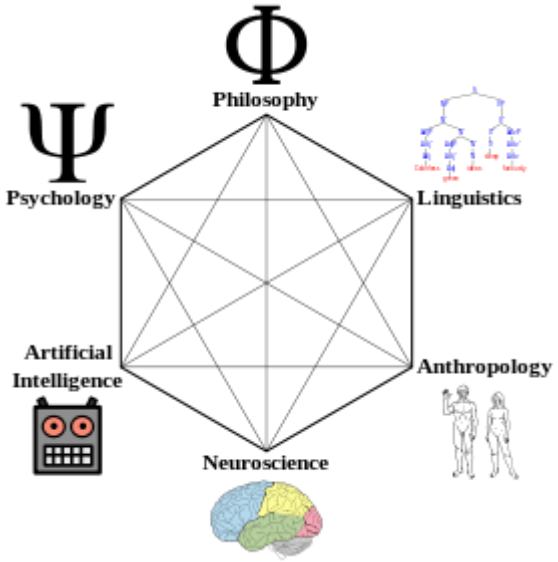

Figure 1.3: Fields of Cognitive Science [25]

1.5 Classification of Intelligent Tutoring Systems

Intelligent tutoring systems can be categorized into three types [27]:

I. **Model Tracing Tutors**: Model Tracing tutors are based on the concept of "Model Tracing" where expert module is held responsible for checking the learner's actions. The domain knowledge in the expert module in this type of tutors is stored in the form of production rules. It detects errors when a student's action either matches to a production rule (in knowledge base) representing a wrong step or if it fails to match any production rule, then this enables the tutor to provide feedback for each step taken by the student while solving a problem.

II. **Constraint-based Tutors**: In Constraint based Tutors, the domain knowledge is stored as constraints. A constraint consists of three parts: a

relevance condition that describes the instant when the constraint is valid, a *satisfaction condition* that specifies the other tests or condition which must be true and a *feedback message* allied with the constraint. This type of tutor isn't bothered by the history of actions performed by the student but the current state of the student. As long as the student doesn't go into a wrong state, he is not restricted from the actions he performs. Constraint based tutors involve a higher level of generalization which result in lesser domain modeling, which results in lesser authoring effort.

III. **Example-Tracing Tutors**: Example-Tracing Tutors assess student's actions by comparing it with examples of right and wrong problem solving actions. They are able to provide guidance at each step. They are able to tutor complex problems having multiple correct solutions. These types of tutors are comparatively easier to develop than model-tracing tutors, other than that it is very difficult to differentiate between both of these type of tutors [16].

1.6 Why Intelligent Tutoring Systems?

There are certain advantages of Intelligent Tutoring Systems over human tutors. Some of them include cost efficiency, tutoring advantages, personalization, and availability.

In conventional teaching methodology, personalization can be attained only by the means of one-to-one teaching but certainly it is not an ideal way in terms of physical space and financial limitations.

The cost involved in operating an ITS is significantly lower than a traditional classroom teaching. ITS only involves funding amount for the purchase of hardware and software support. It is experimentally proven that approximately 63% cost is reduced if the instruction is provided by the use of technology [36]. In addition to this, it is cost effective to bring instructions to learner rather than bringing learners to school (as in conventional teaching).

Also, intelligent tutoring systems try to capture the best features of the conventional teaching methods and add on certain special features including continuous evaluation of the student throughout the learning process, providing

hints and giving learners sufficient space and time to solve out the problems by themselves [31].

1.7 Organization of Thesis

The work in the thesis is organized as:

Chapter 2 describes the background of the Intelligent Tutoring Systems and the Literature Survey regarding the evolution of the ITS and current trends being followed in the development of ITS. Chapter 3 describes the problem statement and the objectives to be achieved. Chapter 4 illustrates the proposed methodology. Chapter 5 describes the experimental results and Chapter 6 concludes this work with discussions regarding the future research scope.

CHAPTER 2

LITERATURE SURVEY

Significant amount of research has been done over the past decades in the fields of artificial intelligence and machine learning. One of the major achievements of this research has been the development of Intelligent Tutoring System. It's been a major milestone in the amalgamation of technology with education. These systems have offered various research areas which are continuously addressed by various researchers. This section describes the evolution of ITS from the early 1970's till present date systems.

2.1 Background

The beginning of technology assisted education tools dates back to the 1960's and the term coined for these tools was "Computer Aided Instruction (CAI) Systems". Example of such a tutoring system was UHR developed in 1969 which was build for the domain of arithmetic problems but this system lacked user modeling and adaptation features. These systems were built for individuals with low aptitude and were considered to be educationally fashionable and were moving towards more structured and goal oriented instructions [36].

In the early 1970's, ITS or rather CAI Systems' development took a new turn and involved Knowledge Representation techniques, Student Modeling , Strategic Tutoring , Genetic Graphs, Buggy Library and Expert System development[8].

In 1980's, the emphasis was made on causal reasoning abilities, evolution of rational models, simulations, natural language processing , authoring tools and systems build on the concept of model tracing. In 1982, Sleeman and Brown coined the term "Intelligent Tutoring Systems" for the new evolving systems. They defined ITS as computer based problem solving programs, laboratory instructors, coaches and consultants. And for the first time artificial intelligence was used in these systems which made them "intelligent" [38].

In 1990's, spotlight shifted to concepts of Learning Theory, Collaborative Learning against Individual Learning, Information Processing and Virtual Reality [14].

The beginning of 21st century led to astonishing developments in ITS and it still continues. Research was made on efficient Student Modeling, Learning through games, adaptation to emotions and psychological state of the learner, Web based Tutoring Systems, usage of Fuzzy Logic, Summarization Systems, Motion Capture Technology, Educational Data mining and Cognitive and Meta-Cognitive abilities [8].

2.2 Categories of ITS

This section of literature survey summarizes the popular ITS developed in various fields or domains.

I. Programming Language Tutors:

MENO project was developed in late 1970s' at the University of Massachusetts to tutor PASCAL to novice programmers. The goal was to detect syntactic errors in simple programs and then connecting these errors to determine the underlying misconceptions and then tutoring the students about the misconceptions [39].

BRIDGE is another ITS developed in 1980's designed to provide a complete programming tutorial environment for novice programmers. It involved tutoring by three phases. In the first phase, student constructs programming instructions in English language phrases. In the second phase, student matches these natural language instructions to programming plans. In the final phase, student matches plans to programming language constructs and develops a programming language solution to the given problem [38].

Other tutors include SQL tutor and C++ tutor to teach SQL and C++ respectively.

II. Medical Diagnosis :

Medical diagnosis is considered to be the best field for development of expert systems. Few attempts have been made by the developers in this particular domain .

GUIDON developed by Clancey in 1979 was interfaced with MYCIN for tutoring [41]. MYCIN is an expert system in which the domain knowledge is stored and represented through production rules. In a tutorial session of

GUIDON, student plays the role of a medical consultant. Tutorial module of the GUIDON presents a medical case to him with various symptoms experienced by a virtual patient. The student is expected to ask for the related information in medical terms. GUIDON then compares the questions asked by the student to that of MYCIN. This type of teaching methodology is called as "Case Method Tutoring" [42].

III. Simulations:

Simulations are being used from a very long time. They are built on the notion of "Learning by Doing". They allow students to learn while performing a virtual version of an actual task. Students practice the given tasks on the simulators while receiving instructions from ITS.

STEAMER developed in 1984 is an interactive simulator based on computer graphics and is used to train the engineers who operate steam propulsion systems in large ships. It displays a running model of the propulsion systems through animations and thereby learning all the procedures to operate the actual plants [40].Figure 2.1 shows a snapshot from STEAMER.

The following methodology was used for simulations in tutoring:

- Each component had a description in terms of an abstract device.
- Abstract procedures are associated with the abstract device to provide feedback to the student.
- The sequencing of steps in these procedures can be described based on technical constraints imposed by the abstractions.

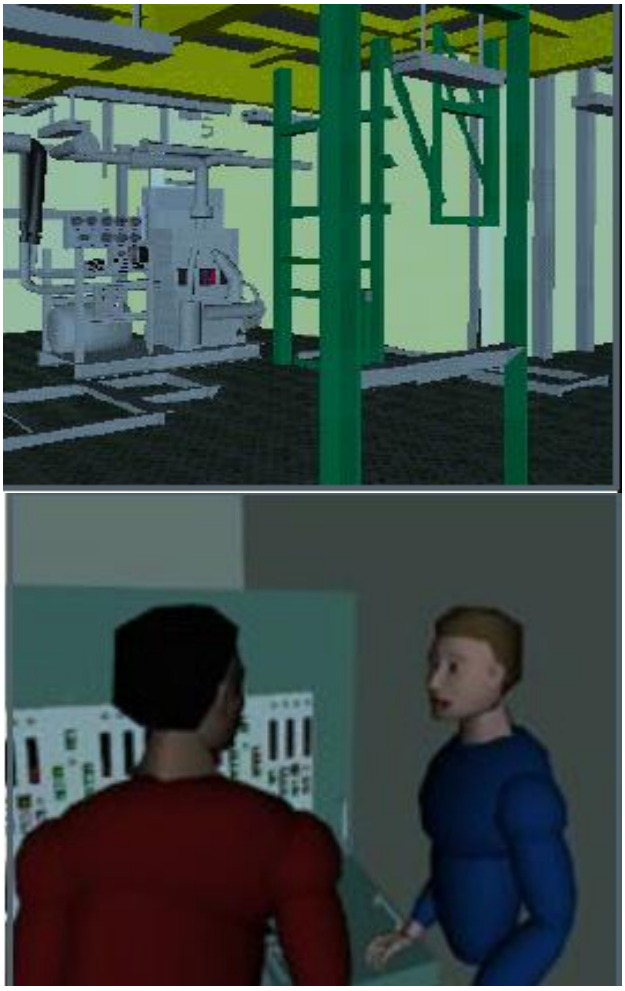

Figure 2.1: A snapshot from STEAMER used in US Navy [40]

IV. Gaming Environment :

This type of ITS incorporates the notion "Learning while Playing" and is considered as the easiest way to learn a domain subject [14].

WUSOR developed in 2002 by Goldstein is an ITS which trains for the popular game WUMPUS. It has three versions developed over successive years. In the game, the player is initially located somewhere in the maze of caves and has the aim of killing wumpus who is also located somewhere in the same maze. There are several difficulties in finding the wumpus like presence of bats, pits and the wumpus himself. Pits and wumpus are deadly; bats shift the player to a random cave elsewhere in the maze. Now, the player has to infer the probable location of wumpus and the dangers from the warning he receives from the tutoring module of the WUSOR. The wumpus

can be sensed two caves away and he is able to shoot wumpus from that much distance. To win the game, the player must shoot one of his five arrows in to the wumpus nest. The player can lose if he falls into the pit or by walking into the wumpus nest or if his arrows are finished without any one hitting the wumpus [38].

V. Mathematical Problem Solving:

The availability of well defined structured approaches for solving mathematical problems are the major reasons that majority of ITS are developed in this field.

WAYANG which was developed in 2009 is an ITS including adaptive help and multimedia for approximately three hundred mathematical problems. It is used by more than four thousand middle and high school students. It digitally evaluates the problem difficulty and records the student responses and provides support accordingly. According to reports, 10-16% more students have passed the state exam in US [36]. Figure 2.2 describes step by step evaluation in a Mathematics tutor.

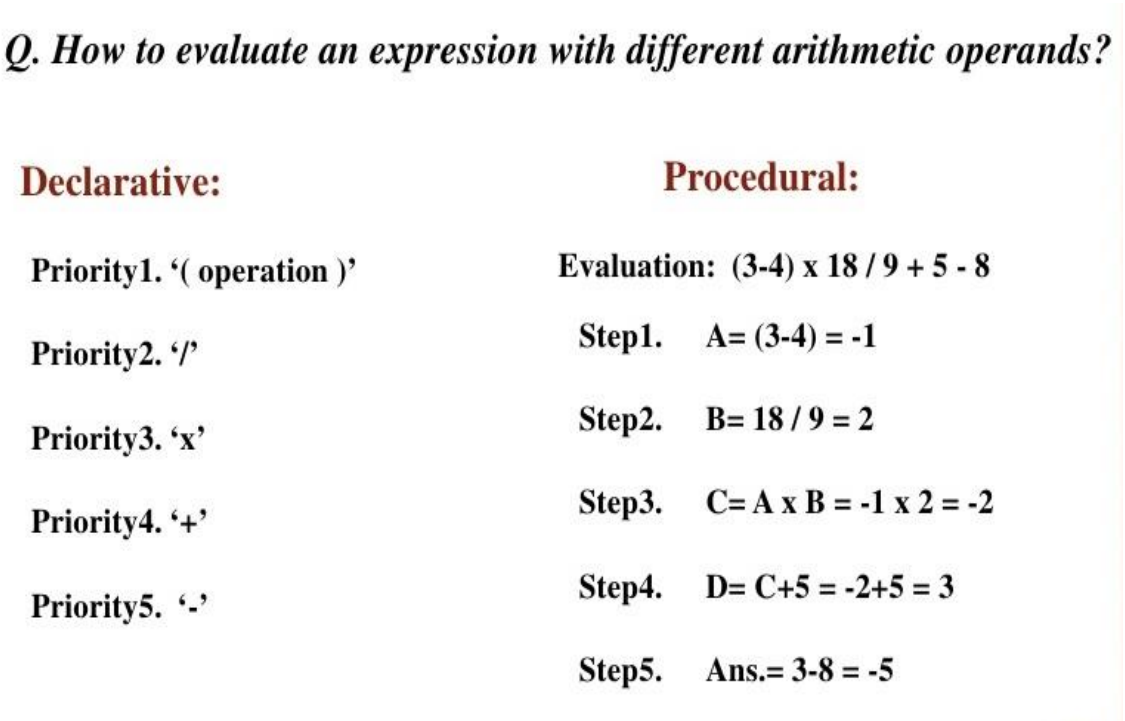

Figure 2.2: An example of a Mathematics tutor

The tutor makes the student solve a problem step by step and allows him to ask for help anytime he wants. The answers of the student are evaluated at each step. If the student makes a mistake, it is pointed out to the student and the student is allowed to modify his response or seek help from the system. If the student is unable to solve the given problem, the system displays the solution and poses next problem similar to the previous one.

2.3 Current Trends in ITS Development

In the recent years, the major research is being done to provide adaptivity and personalization in ITS. Also, ITS is now being developed as a part of Educational games , Mobile application and standalone educational applications [29].

Adaptivity and personalization can be described as the ability to modify the tutoring procedure as per the student's needs, knowledge, learning preferences, and psychological state. Searching efficient methods for providing the same is a challenging task for the researchers and developers nowadays.

The major methodologies introduced over the time are Overlay Model, Stereotypes, Machine Learning techniques, models enabling Cognitive theories, Constraint Based Models, Fuzzy State theories and Ontology based Student Modeling [8].

Overlay Model assumes that student has correct but incomplete knowledge of the mentioned domain. These models are said to be inappropriate for the sophisticated models as they do not consider the way in which users make inferences. The extensions to overlay model have also been made known as Perturbations which consider all the misconceptions as well as allows a better way to diagnose learner's errors and to provide appropriate remedial measures to it [44].

Stereotypes are a part of user modeling, initially used in the system GRUNDY [42]. The concept behind stereotyping is to huddle all the possible users into groups on the basis of common behavioral traits and learning characteristics [43].

Machine Learning techniques are used to provide automation for adaptivity.. Machine learning allows formulation of several models from the observations and has been studied extensively to achieve automated induction [46].

The Constraint Based Model is developed on the concept of "Learning from errors and mistakes" and assumes that a learner will make mistakes even if he had been taught correctly and thus imposes constraints so as to minimize those errors [45].

Fuzzy Logic is based on the notion that uncertainty exists and is caused by incomplete information and thus focuses on moving the uncertainty in any concept to certainty [50].

The cognitive theory is based on various other domains such as artificial intelligence, psychology, physiology, neurology etc. It attempts to explain the way humans think and interpret things. Several methods have been proposed to analyze student's psychological and physiological state [15]. Figure 2.4 describes the involvement of various cognitive measures involved in ITS. Some of them have been stated below:

i. **Eye Gazing Technology:** This technology involves analyzing the eye movements by either detecting the point of gaze or the motion of an eye relative to the head. For this purpose a device named as eye tracker is used which stores the eye gaze positions at frequent time instances and then analyze the gaze patterns to identify when the student gets bored or disengaged. The system then tries to reengage the student by the use of certain dialogue based interaction and asks the student to try to focus more. Disengagement is recorded when the student looks away from the screen for a long duration. This helps in improving the focus and concentration of the learner [47]. Figure 2.3 describes the flowchart of the eye gaze technology embedded ITS.

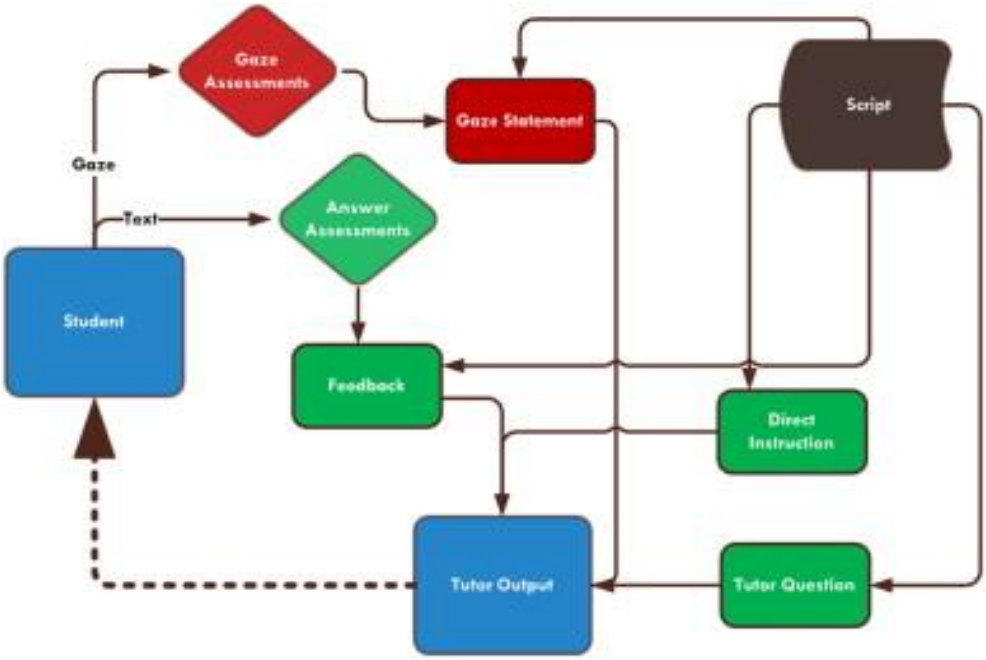

Figure 2.3: Flow diagram for Eye gazer based ITS

ii. Facial-Expression Analysis: This process involves using a web cam to identify the movements in facial muscles by comparing several images of the learner captured through the webcam. These types of systems are highly efficient to analyze the affective states of the learner and then successfully adapting to the tutoring methodology accordingly [48]. But there are several challenges associated with it such as lots of real time image processing and parallel processing with the knowledge evaluation and that increases the complexity of the system.

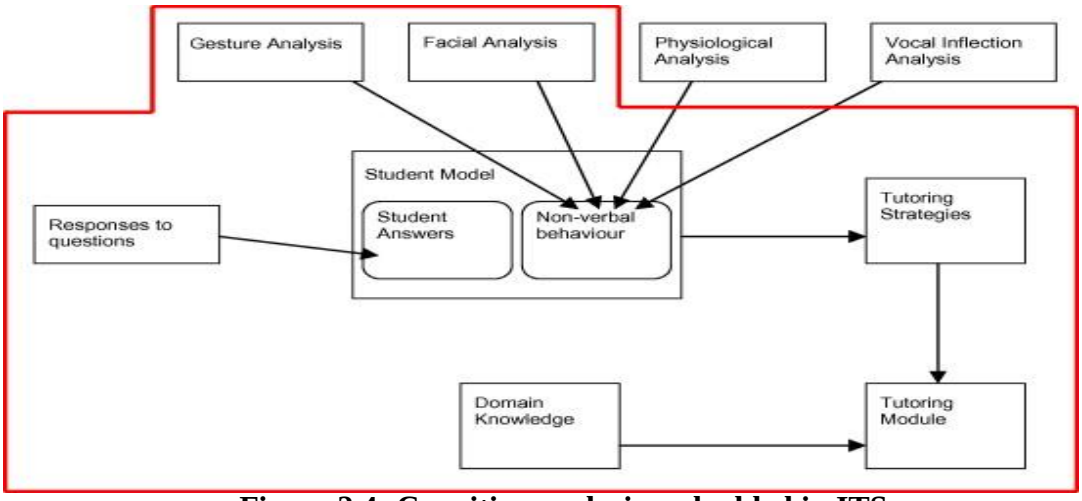

Figure 2.4: Cognitive analysis embedded in ITS

iii. Physiological and Psychological tools: These are the sensors used to measure the person's physiological responses. Usually the person's current state is anticipated within an emotional space with the dimensions involved such as arousal, intensity, control etc. Most of these are measured using the recordings of the electrical signals generated by brain, heart, muscles and skin [49].Physiological sensors provide an objective measure of the psychological sensations .The major advantage of these sensors is that they enable the continuous monitoring of the learner's state. Limitations being complexity of the design, increased cost and technical expertise required to handle the sensors operations. Some of the sensors are:

a. Electromyogram (EMG): Measures muscle activity.
b. Electroencephalography (EEG) : Measures neuron activity
c. Electro dermal Activity or Skin Conductance (EDA or SC): Measures the hydration level in the layers of the skin and is generally recorded from the surface of hands or wrists.
d. Electrocardiogram (EKG or ECG): Measures heart activity including heart rate, inter-beat interval or variability in heart rate.ECG can be analyzed to detect stress and confidence level of the learner.
e. Blood Volume Pulse (BVP): measures blood pressure.

2.4 Cognitive Factors effecting Learning Outcomes

Methods involving machine learning are used for user modeling. According to the researchers, the student module should include Cognitive capabilities, user's preferences, Behavioral traits and characteristic features [4].

The model should include the learner's Demographic data. User's characteristic features are determined by the parameters such as Intelligence Level, Motivation Level, Self-Confidence level, Level of Anxiety and Self Declaration of skills [5].

Ontology based method is also used for recommendation of learning material. The parameters used are: Knowledge level, preferred form of Learning Style, Goals of Learning and Language Preferences [3].

Learner's behavior is modeled with Logical rules of if-then form [1].

One of the most popular model for determining the learning styles is the one developed by Felder-Silverman [6]. Few researchers argue that this model is the most suitable model for providing efficient adaptivity.

The problem of adaptivity can also be analyzed by considering cognitive traits of a learner. Some other factors like Information Processing Speed, Working Memory Capacity also plays a major role in determining the degree of personalization. For example a student with low working memory capacity should avoid "Cognitive Overload", hence, the learning environment should consist of detailed explanation of the concepts to be taught and unnecessary information must be exempted.

Many scholars and researchers have mentioned that Learning Strategies and Motivation have strong impact on the learning efficiency.

Another important factor is Brainpower and the Knowledge state, higher the knowledge, the better results in learning. Knowledge state can be determined by the idea of conducting a Pre-Learning Test [18].

2.5 Present Variations of ITS

Let us consider a few variations of ITS developed in present scenario:

Adaptive Intelligent Web Based Education Systems are a substitute to the traditional e-learning environments. These systems utilize networked computer systems with sensors embedded in them to record significant bio-signals and emotions and then adapting to the student's mood. Tutoring in these type of systems is based on case based modeling and the cases being angry, confused, frustrated. [33]

Automatic Summary Assessment has been a highly accepted mechanism. Various techniques such as Latent Semantic Analysis, N-Gram Co-occurrence etc. have been proposed to support Automatic Summary Evaluation. LSA was developed by Landauer in late 1980's for the intention of document indexing and information retrieval [25], [51].

Handwriting Based Intelligent Tutors use input in form of hand written matter that offer several affordances for students that traditional typing based interactions do not [29].

Educational Data Mining is apprehensive with researching, developing and then using the automated methods to detect access patterns of student in the educational data that is difficult to analyze manually because of large volumes of data that exists [52].

Motion Capture technology is popularly being used in Automated Lesson Generation Systems. One of the system being "Dance Learning from Bottom-Up Structure" (DL-BUS) which guides beginners to learn basic dance movements. This system involves two phases: In first phase smaller steps are taught and then in second phase those smaller steps are combined to form dancing patterns providing appropriate cognitive load and hence an efficient learning environment [53].

CHAPTER 3

PROBLEM STATEMENT AND OBJECTIVES

Intelligent Tutoring Systems are more acceptable and popular because they can improve the performance of the learners, simulate cognitive development, offer adaptivity to the student's need and preferences and thus reduce the learning time for students. These systems place the learner at the centre throughout the learning process and offer a good degree of personalization to the learner which was a major drawback in the conventional one-to-many teaching process. The basic foundation of the ITS is effective user profile modeling that helps in uncovering student's skills and needs.

3.1 Research Gaps

I. Lack of analytics in determining the initial knowledge state of the student

The present Intelligent Tutoring Systems do not assess the student's domain knowledge of the learner before beginning the learning process. Due to this same study material is provided to all the students irrespective of their current knowledge state. It is not necessary that every student who registers to the ITS will have the same initial knowledge level and thus learning scenario involving difficulty level of the questions posed to the learner, learning material , hints and explanations, time to solve problems should be different for each student. So, it is necessary to evaluate the current knowledge state of the learner before beginning the learning process.

II. Ignorance of the contemplation of the cognitive abilities of the learner

The cognitive abilities such as working memory capacity, verbal, spatial and numerical reasoning are significant to investigate in addition to domain knowledge. Domain knowledge can be applied in a particular domain only while cognitive abilities can help a student outclass in any domain because they are domain independent.

3.2 Problem Statement

Lack of personalization and adaptivity is the major issue in the present scenario in the field of ITS development and operations. So, there is a need to identify efficient methods to determine the initial knowledge state and the cognitive skills of the learner so that ITS is able to offer sufficient adaptivity and personalization to each learner.

3.3 Aims and Objectives

The aim is to develop a model that will analyze every student’s cognitive skills, psychological state and initial knowledge level before beginning the learning process. Cognitive abilities determine a person's typical style of understanding, perceiving, thinking, remembering and problem solving. The information of differences among people is valuable especially in educational environment because a student’s performance may enhance or decline depending upon the used teaching methodologies. If cognitive abilities of a student are considered in an ITS before presenting tutorials, feedback and hints then that can help in more efficient System-Learner interaction.

CHAPTER 4

PROPOSED METHODOLOGY & IMPLEMENTATION

User's profile modeling is an important element for providing adaptivity and personalization. In Intelligent Tutoring System, a learner can be described with features such as Actual level of Knowledge, Personal Traits, Interests, Cognitive abilities, Meta-Cognitive abilities, preferred Learning Styles [5].

4.1 Selection of Cognitive Parameters

This work focuses on a concept build on the notion of Cognitive Science based on the data describing student's Behavioral Traits and Features, is able to predict the Learning Outcomes. Each learner can be described using certain characteristic features such as student's Personal Information, Styles of Learning that is most effective for him and his Behavioral Characteristics.

The characteristics of a student's behavior are determined by the following attributes:

I. **Initial knowledge level:** Initial knowledge level helps in determining the level of concepts that needs to be taught to attain desired level of knowledge after the learning process has ended. The initial knowledge level is judged through a test taken prior to learning process and is termed as Pre-Learning Test [13].

II. **Motivation level:** Motivation level reflects the learner's willingness to learn or motivation impacts the amount of efforts a learner will put in so as to learn. According to researchers, an optimal level of motivation is medium which positively affect the learning outcomes [28]. Accordingly, one of the important factor in the design of ITS is to support the arousal and persistence of student's motivation to learn. Motivation level is judged through a Psychological Questionnaire [57].

III. **Concentration level:** Concentration level is considered as an important factor in the efficient learning for the learner. More the concentration, lesser will be the learner distracted and more focused he will be during the learning process [31]. This factor also determines the time taken to learn

the desired concept. Concentration level is judged through a Psychological Questionnaire [55].

IV. **Learning Capability or Grasping Power:** Learning Capability tells us about how quickly learner will learn the concept and lesser will be the time required in the learning process [34]. Grasping power is judged through a mental speed test. This is a time constraint based test termed as "Mental speed Test" and involves questions on image to word mapping and basic arithmetic calculations [56].

V. **Importance of task to the learner:** Importance of task will be self assessed by the learner and determines the willingness or zeal of the user to learn [45].

4.2 Working of Proposed Methodology

STEP 1: Student logins in the system and fills out the demographic data.

STEP 2: Student gives the Concentration Test, Motivation Test, Mental Speed Test, Pre-Learning test and assesses the Importance of Task to him.

STEP 3: Learning begins according to the preferred learning styles.

STEP 4: Student takes the Post-Learning Test.

STEP 5: Student is classified into a suitable class according to the results obtained.

This entire procedure creates a dataset with the values of parameters mentioned above that describes a student. Finally students are classified to an appropriate class based on the results of their Post-Learning test. This concept is presented in the Figure 4.1.

The Learning Style is determined by Felder –Silverman learning styles [22]. A Felder and Silverman learning styles model considers that every student's learning style can be jointly depicted by four sets consisting of two bipolar values:

[{active, reflective}×{sensitive, intuitive}×{visual, verbal}×{sequential, global}].

The classifier used for classification and prediction purposes is Naïve Bayes Classifier supporting Kernel Based Distribution. Students are classified into Beginner, Medium and Advanced class based on the data provided.

This classification shall be used to determine what initial learning scenario should be. Students classified as Advanced could be provided with more conceptual knowledge and additional learning material where as students less capable shall be given more time for learning, more explanations could prove beneficial for them [36]. In this way personalization and adaptivity as per the student can be implemented more effectively in ITS.

Such solutions are necessary to develop an optimal path of learning for the student. Also the data such as motivation level, concentration level could also be analyzed and used to enhance the student's learning experience. Student with low motivation must be encouraged throughout the learning process, for example by proving certain reward points on answering a question correctly or some other ways. Also this could help in recommending a student to join a collaborative learning group with similar skills and interests

.

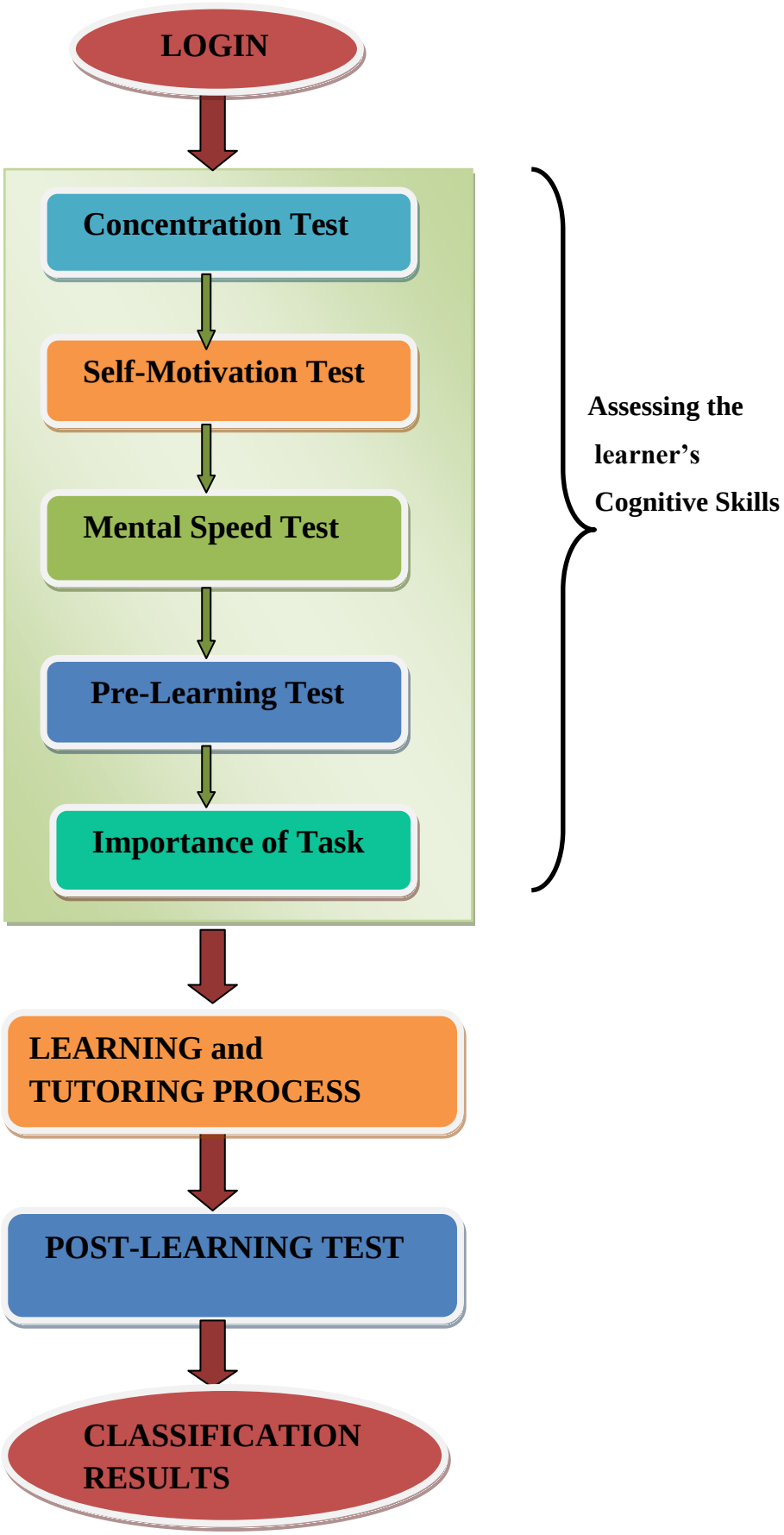

Figure 4.1: Flow chart of Proposed method

4.3 Proposed Contents of User's Profile

User's profile is a necessary component of ITS. It must contain necessary data for providing personalization and adaptivity to each learner. In the proposed approach, it is assumed that a student's profile contains five broad groups of data:

I. Demographic data
II. Personal traits
III. Learning Styles
IV. Behavioral characteristics
V. Generated data

Formally, a student can be represented as a tuple of values defined as follows:

$$t: A \rightarrow V$$

where:

A - Finite set of profile attributes

V - Attribute values

,

$$V = \bigcup_{a \varepsilon A} V_n \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. \quad (4.1)\ [5]$$

$$\bigvee_{a\,\epsilon A} (\mathrm{t(a)}\varepsilon \mathrm{Va}) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \quad (4.2)\ [5]$$

The detailed content of learner's profile is presented in TABLE 4.1

TABLE 4.1: USER PROFILE CONTENTS

Attribute Name	**Attribute Domain**	**Type of data**
Demographic data	Set of data	Demographic data
Motivation Level	{Low, Medium, High}	Behavioral characteristics
Knowledge Level	{Beginner, Medium, Advanced}	Behavioral characteristics
Concentration level	{Low, Medium, High}	Behavioral characteristics
Mental Speed	{Low, Medium, High}	Behavioral characteristics
Importance of task	{Low, Medium, High}	Generated Data
Pre-Learning Test	[0,10]	Generated data
Post-Learning Test	[0,10]	Generated data

The set of demographic data can be described as in TABLE 4.2:

TABLE 4.2: DEMOGRAPHIC DETAILS OF USER

Attribute name	**Domain**
First Name	Sequence of alphabetic characters
Last Name	Sequence of alphabetic characters
Login	Sequence of alphanumeric characters
Password	Sequence of alphanumeric characters
Contact number	Sequence of numeric digits
Email address	Sequence of alphanumeric characters
Age	{Young, Adult, Old-age}
Preferred Learning time	{Morning, Noon, Evening, Night}
Level of studies	{Primary, Secondary, Undergraduate, Post-Graduate
Field of knowledge	{Humanities, Science, Technical, Chemical, Others}

4.4 Predicting Learning Outcomes

Naïve Bayes Classifier is used for predicting the learning outcomes of the learner. Naïve Bayes Classifier is a simple classifier based on the probabilistic concepts for the classification purposes which assumes strong independence between the parameters or features considered [7].Even if these features depend on each other or upon the existence of the other features, all of these properties independently contribute to the probability and that is why it is known as ‘Naïve’. This classifier is easy to build and is very useful especially for large datasets. This classifier is known to surpass several other complex classification models [54].

For the prediction of learning outcomes in the proposed model, factors: Initial Knowledge level, Motivation level, Concentration level, Mental speed or grasping power, Importance of task are most imperative and have a strong influence on the Learning Outcomes.

All this information is used to represent each student by a vector Y, which stores the above mentioned parameters.

$Y = (Y_1, Y_2, Y_3, Y_4, Y_5, R)$where:

Y_1 : Initial Knowledge Level

Y_2 : Level of Motivation

Y_3 : Level of Concentration

Y_4 : Mental Speed

Y_5 : Importance of task

R : Result of Post-Learning Test

Students will be classified into three classes based on the results of the Post-Learning Test. Classes :

- C_1 (Beginner)
- C_2(Medium)
- C_3(Advanced)

These classes determine the students' abilities and Learning Outcomes.

Naïve Bayes' Classifier finds a class C_i for which the probability that a given vector or tuple Y belonging to class C_i is maximum, where $i \in \{1, 2, 3\}$. Formally this condition can be defined as:

$$\max_i [\prod_{k=1}^{3} P(X_k|\, C_i).\, P(C_i)\,], \text{ where } i=\{1,2,3\} \quad \ldots\ldots\ldots (4.3) \quad [55]$$

where:

$P(C_i)$ is the probability of occurring of class C_i, i.e. $P(C_i)=N_i /N$

N_i represents the number of instances that belong to class C_i.

N represents the number of instances in training set.

$P(Y|C_i)$ is the conditional probability of Y belonging to class C_i and can be estimated by:

$P(Y_k|C_i) = (N_{ik}/N_i)$

Where:

N_{ik} is the number of instances belonging to class C_i and with attribute value $Y=y_k$.

The pseudo code for the algorithm used for prediction of learning outcomes is written below.

Procedure 4.1: Pseudo code for Classification Function

Input: TestData of tuples Y; Classes : C_1 , C_2 , C_3

Output: Accuracy of the classifier

```
n:=3; //number of classes
k:=0; // number of instances that are correctly classified;
        for each test instance Yi in TestData do
                calculate P(Ci|Y)>P(Cj|Y) where i!=k;
                if  class:=Ci; then k=k+1;
        maximize P(Y|Ci).P(Ci)
```

The Computational Complexity of the procedure above is O(n).

CHAPTER 5

EXPERIMENTATION RESULTS AND DISCUSSIONS

To show the proposed approach of user modeling, a prototype of ITS is created in the domain of English verb based sentence formation. Six rules will be taught to students during the learning process. The experimental study was performed in two segments:

I. Creating a Dataset (Training data)
II. Using Naïve Bayes Classifier.

5.1 Data Collection:

For creating a dataset, the prototype of the proposed ITS was created using JAVA NetBeans platform. The experimental working of ITS for data collection involved several steps.

STEP 1: The new learner will first register himself with the ITS by filling out certain personal details including name, educational qualification etc. (Demographic data) and will be provided with a username and password which should be entered whenever he logins into the system. Snapshot of login page is shown in Figure 5.1

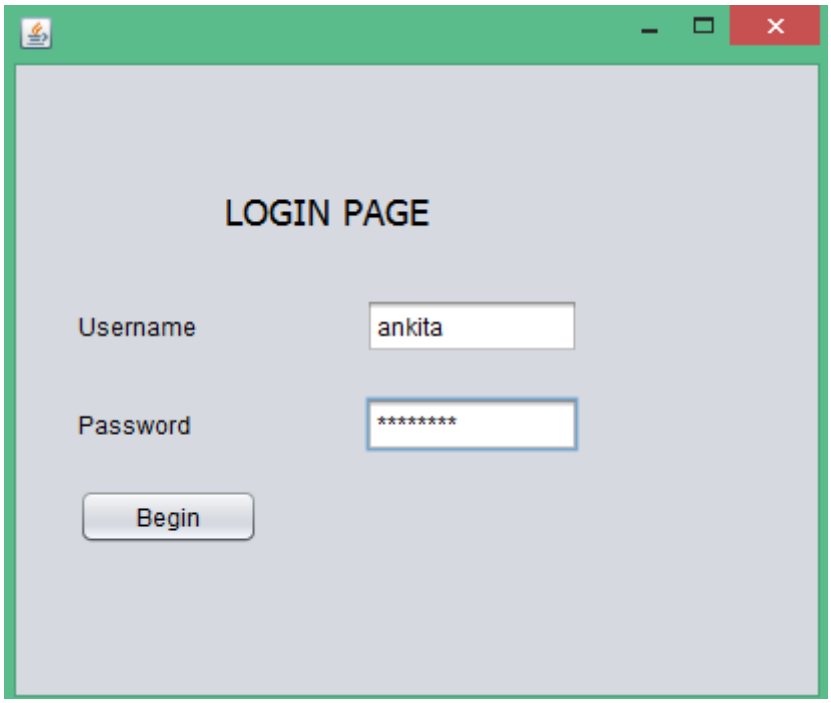

Figure 5.1 Login page

STEP 2: The learner will take the Concentration Level Test (Psychological Questionnaire) and depending on his performance he is classified as Low, Medium or High. Snapshot of a segment of concentration level test is shown in Figure 5.2

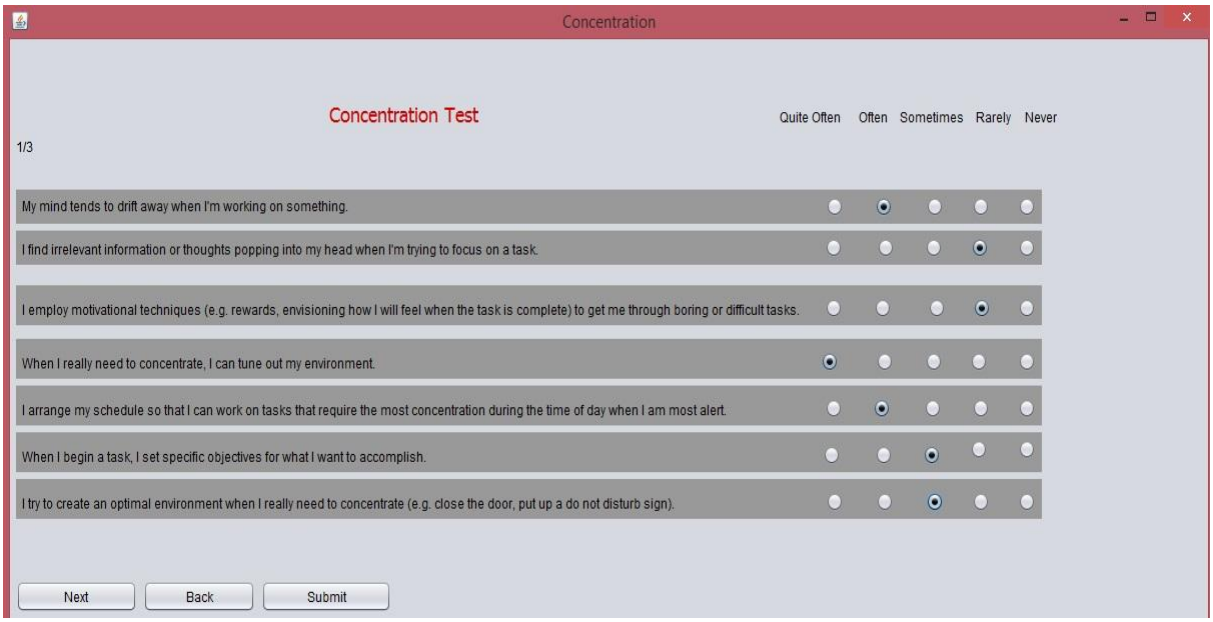

Figure 5.2 Concentration Level Test

STEP 3: Learner now takes Motivation Level Test (Psychological Questionnaire) and again based on his performance is classified as Low, Medium or High. Snapshot of a segment of Motivation Level Test is shown in Figure 5.3

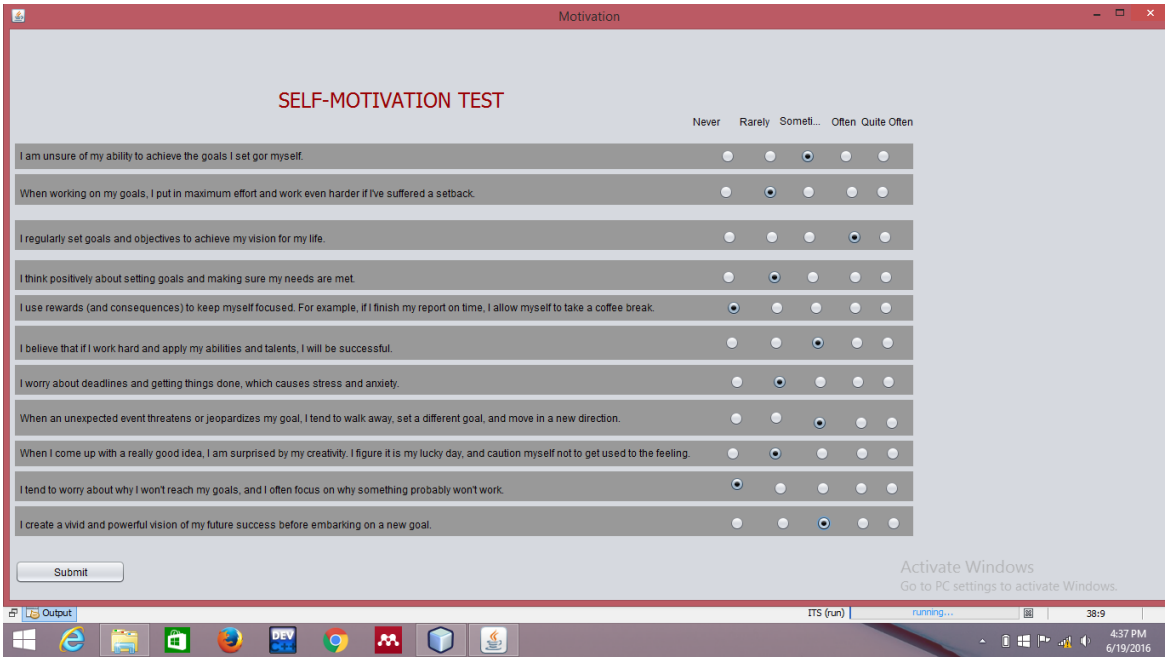

Figure 5.3 Motivation level Test

STEP 4: The learner will now take a Mental Speed Test which is a time based test and will be categorized into Low, Medium or High according to his scores. The test involves three types of questions:

i. Word to Picture mapping as depicted in Figure 5.4

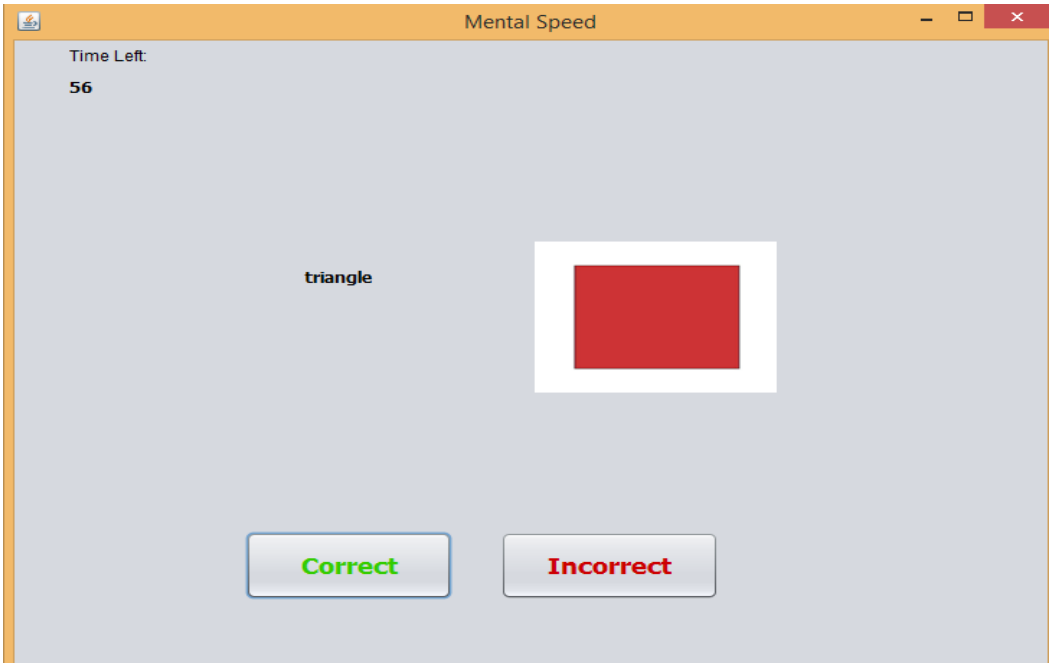

Figure 5.4 Word to Picture mapping

ii. Basic arithmetic calculations and series based questions as shown in Figure 5.5

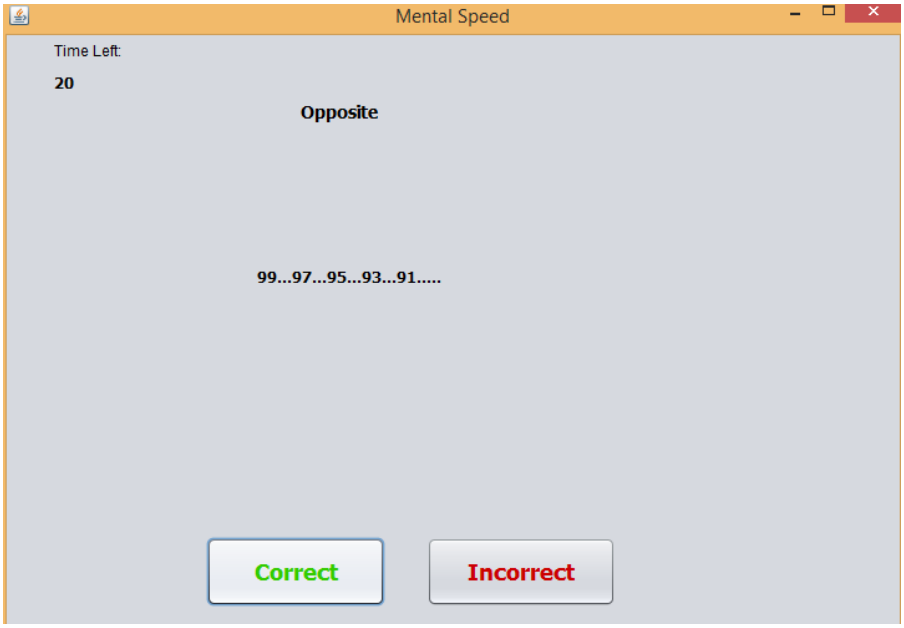

Figure 5.5 Arithmetic questions in Mental Speed Test

iii. Opposite Tag: There is a trick involved in this test which is Opposite Tag. This tag will randomly be displayed with some questions and the learner has to answer oppositely or in other words he has to intentionally mark the wrong answer. This is shown in the Figure 5.6.

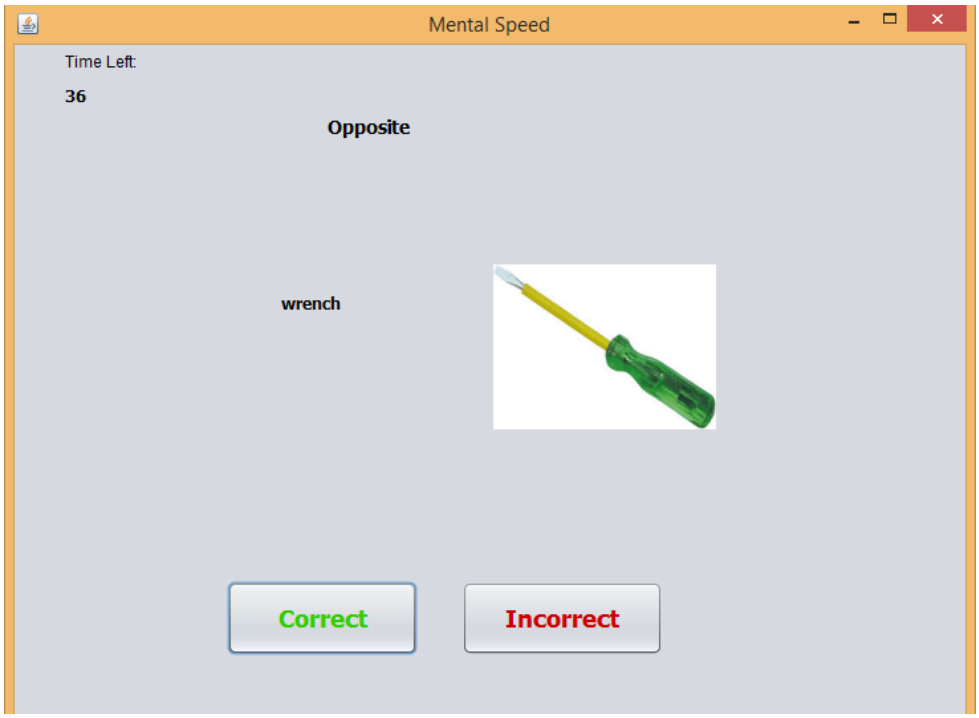

Figure 5.6 Mental Speed question with Opposite Tag

After the time is up, solutions will be automatically submitted.

STEP 5: In this step student gives a Pre-Learning Test and his performance will be evaluated and based on it, he will be categorized as Beginner, Medium or Advanced forming the fourth parameter i.e. initial Knowledge level. A screenshot of a question from Pre-Learning Test is shown in Figure 5.7.

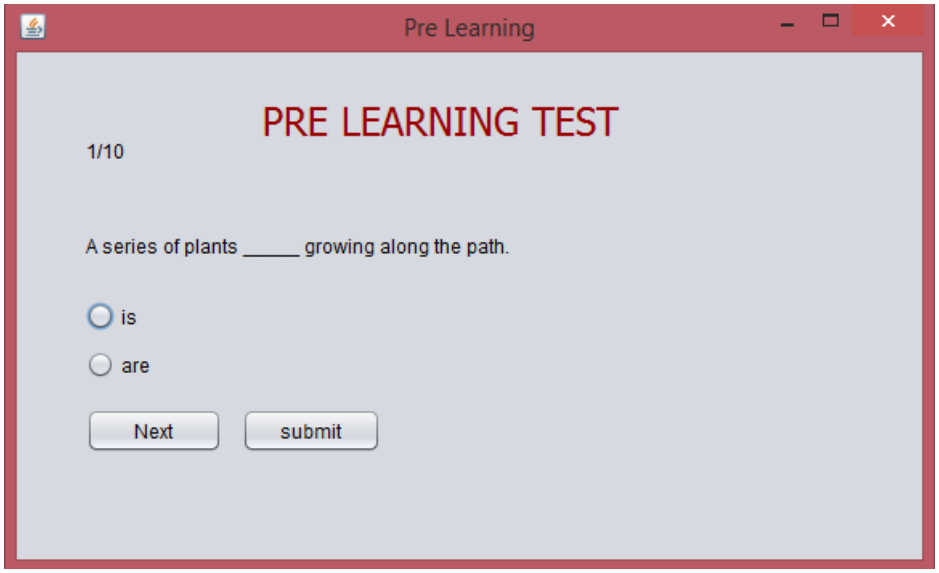

Figure 5.7 Pre-Learning Test

STEP 6: In the final step, student marks the importance of task or importance of learning English to him. Screenshot is shown in Figure 5.8.

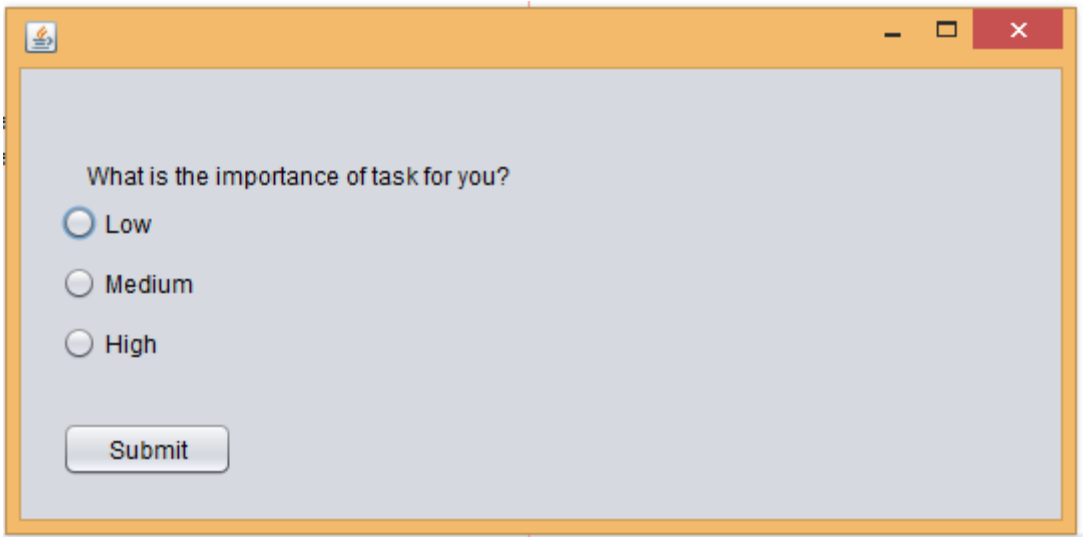

Figure 5.8 Importance of Task

STEP 7: After entering all the required information, learning process begins. A snapshot of the initial display of learning process is shown in Figure 5.9.

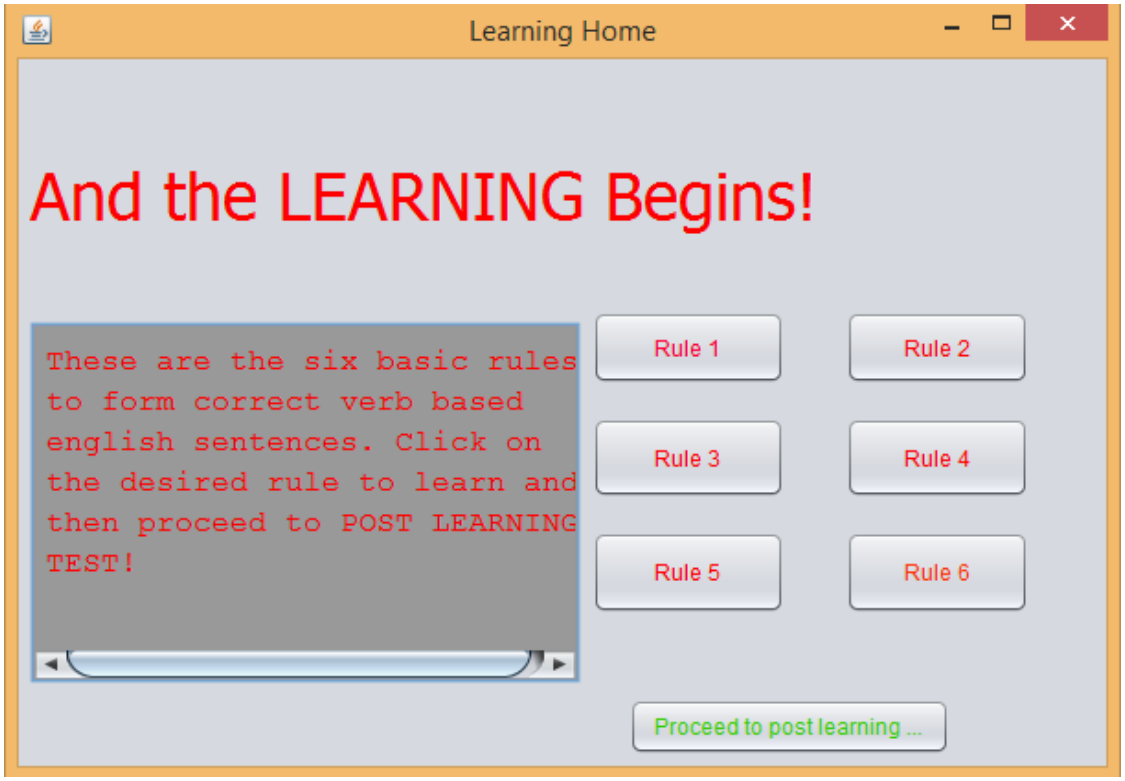

Figure 5.9 Learning Process

The learner selects the rules and then rule is presented to him in textual format. After reading it, he can practice the same rule as depicted in the Figure 5.10.

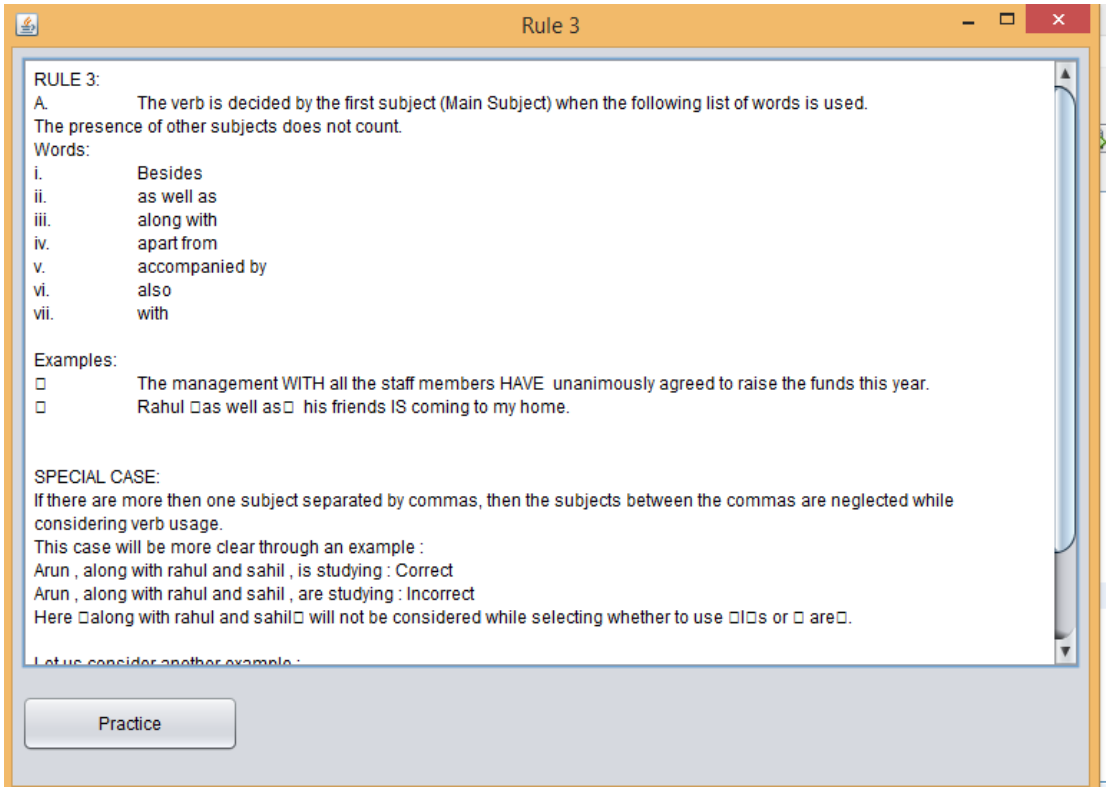

Figure 5.10 English rule selected for Learning process

On selecting practice, a question is posed to him. He can ask for hint by clicking on the Hint button. Hint can be presented him in several forms such as direct concept related hint, motivational hint etc. depicted in Figure5.11 and Figure 5.12

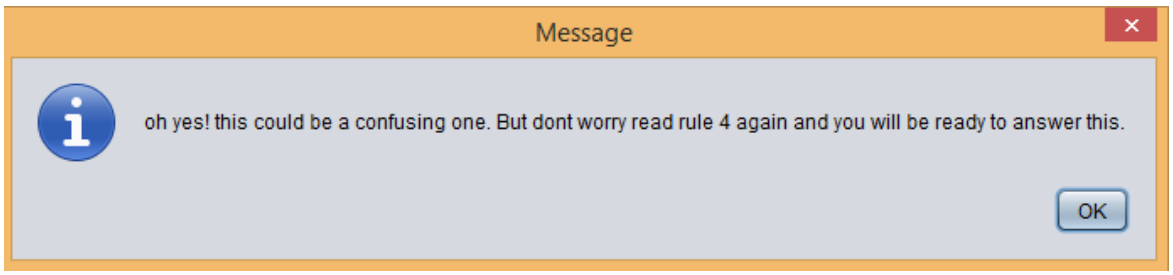

Figure 5.11 Motivational Hint

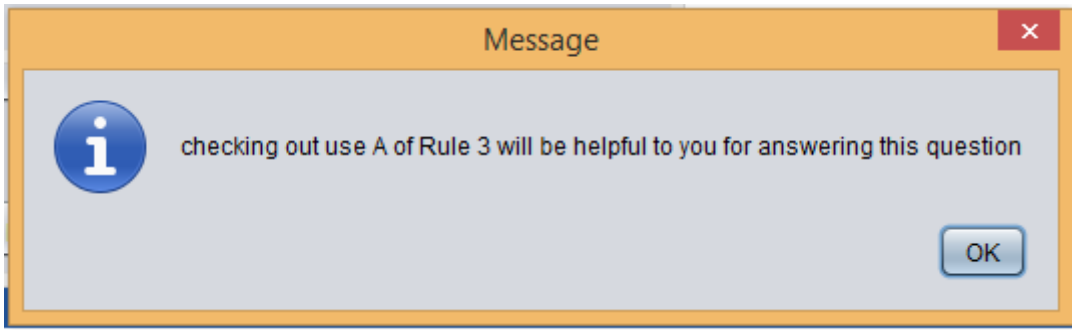

Figure 5.12 Direct Hint

If the learner answers correctly to practice question, feedback is generated as shown in Figure 5.13.

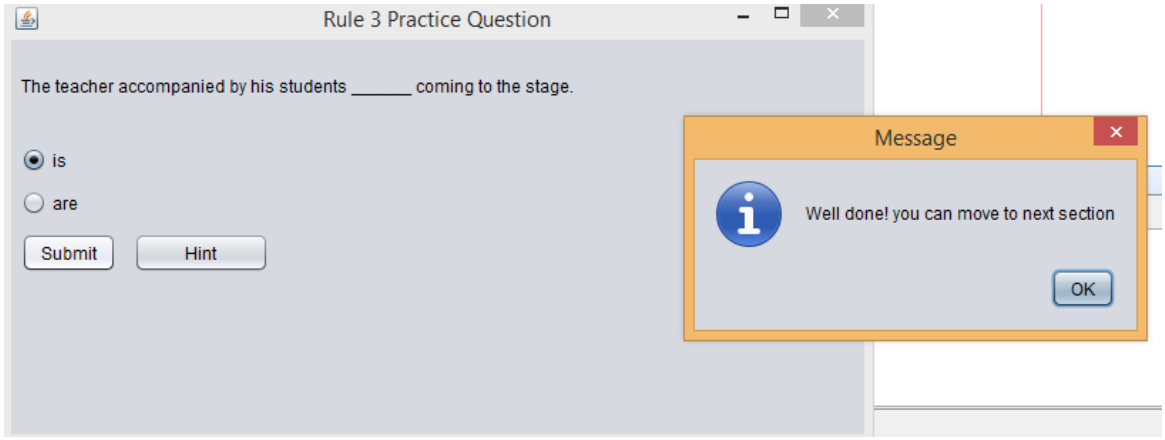

Figure 5.13 Positive Feedback

If the learner answers incorrectly to the practice question, then feedback generated is shown in Figure 5.14

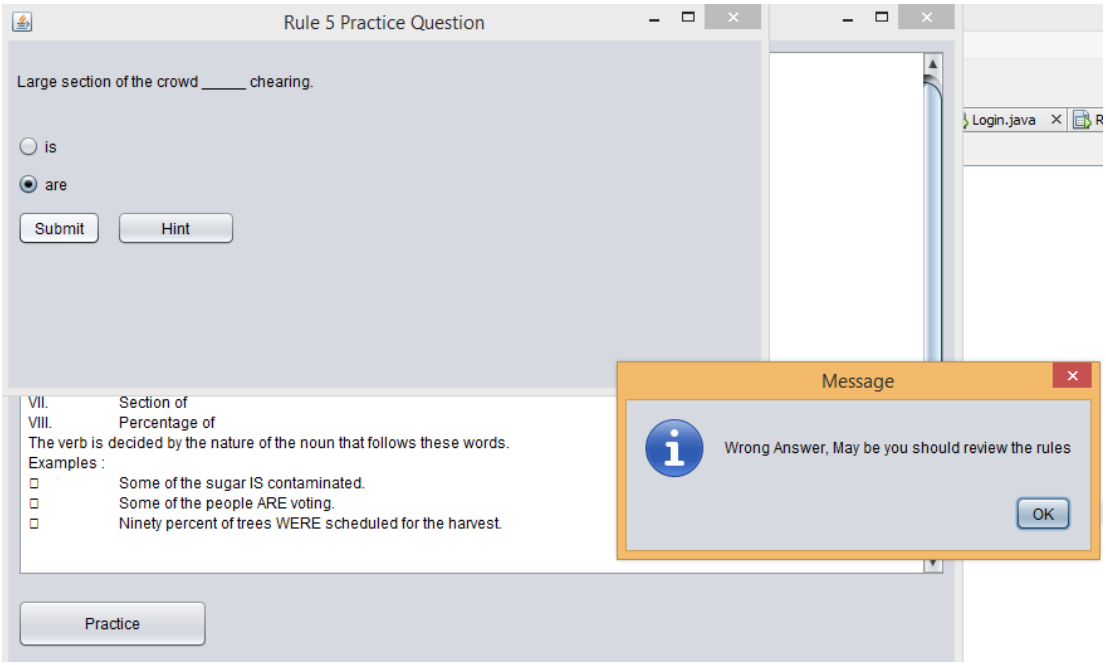

Figure 5.14 Negative Feedback

After the learning has completed, student proceeds to the Post-Learning Test.

STEP 8: In this final step, student gives Post-Learning Test and similar to Pre-Learning Test, is categorized into Beginner, Medium and Advanced forming the sixth parameter value. A question from Post-Learning test is shown in Figure 5.15

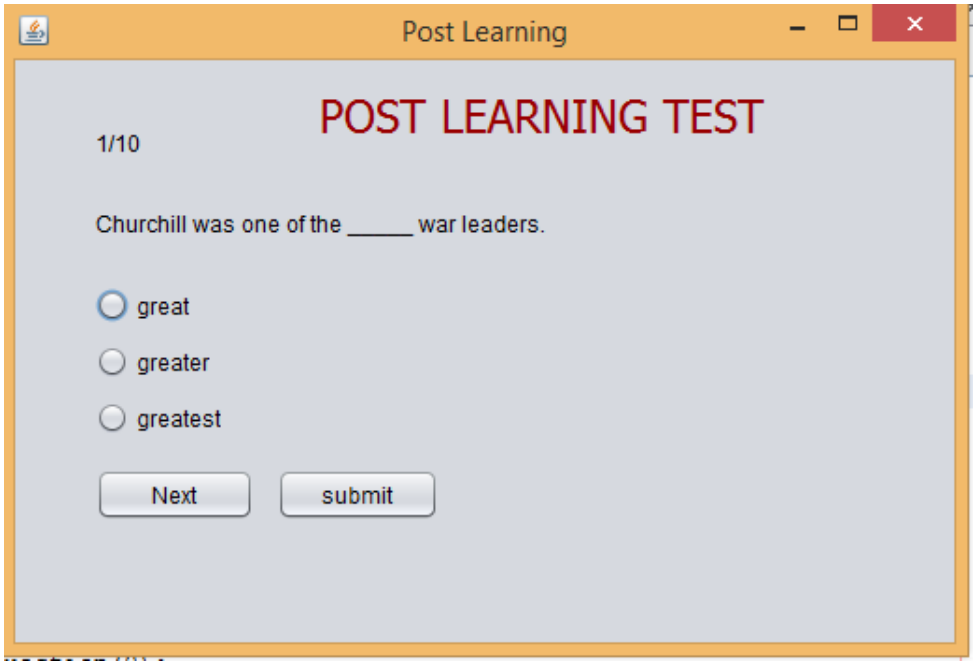

Figure 5.15 Post-Learning Test

For creating dataset, several students were asked to use the prototype of ITS and results which were stored are then used as training set for the next segment of Prediction and Classification.

5.2 Predicting the Learning Outcomes

For prediction, Naïve Bayes Classifier is used and is implemented using MATLAB. Input dataset was divided into 60% training data and 40% testing data. The accuracy of prediction attained is 85%.The prediction results are shown in the Figure 5.16.

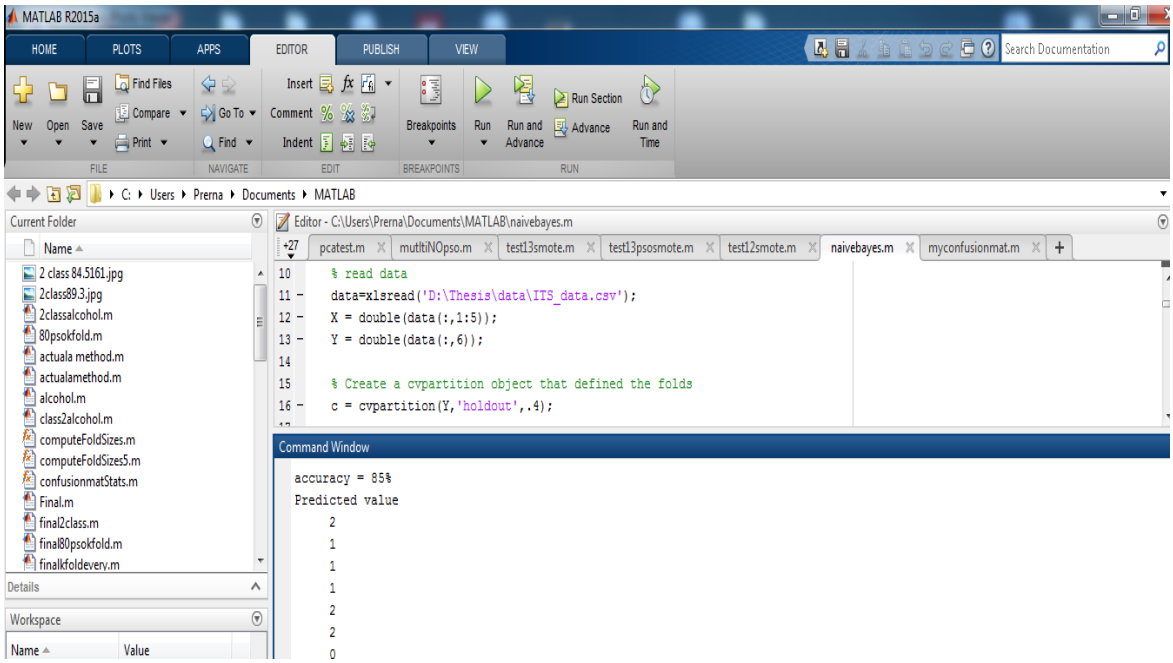

Figure 5.16 Accuracy of the Prediction results

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

7.1 Conclusion

This work proposes a method of User Profiling to predict the Learning Outcomes in Intelligent Tutoring System. Cognitive factors such as Initial knowledge level, Motivation Level, Concentration Level, Mental Speed and Importance of task for the learner have been used as contents of the user profile along with the Demographic data and preferred Learning Styles. Naïve Bayes Classifier has been used to classify the learner in a suitable class and to predict the Learning Outcomes. The accuracy attained is 85% for the predicted results. The proposed procedure is important where determining the initial learning scenario and modifying it according to the learner's preference is required. In other words, Predictive Analytics for determining Learning Outcomes based on the effect of Cognitive Skills of the learner has been proposed in this work.

7.2 Future scope

There are certain factors which need to be considered for the improvement purposes in ITS such as subject areas or the knowledge domain. Areas such as Mathematics, Science and Logic are more suitable for the ITS but subjects involving theoretical concepts such as history, geography, humanities, literature make the design of ITS complicated.

Another aspect that requires attention is the misuse of the Hints Feature. Students rather than putting efforts on solving the problem by themselves, focus on using the hints repeatedly. This hampers the learner's thinking and problem solving capability. So, constraint must be applied on the number of times the hints must be used. Similarly, there must be a constraint on the maximum time that could be spent on a problem. After that the system must intervene and offer hints to the student as after a certain time limit, putting efforts in solving the problem is more a wastage of time rather than useful thinking.

Also concept of meta-cognitive skills is opening up new channels for future research in this area. Meta Cognitive Skills means "Thinking about Thinking". Developing

cognitive skills and meta-cognitive skills is difficult for learners but with the help of artificial intelligence, research has showed that it is possible to improve the meta-cognitive development.

Many researchers feel that performance of the Intelligent Tutoring System will be enhanced if they have the capability to adapt according to the emotional state of the learner. This concept has led to the idea of development of new generation ITS to be known as “Affective Tutoring Systems”.

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LIST OF PUBLICATIONS

- Ankita Juneja and Harkiran Kaur, "Modeling User Profile for better adaptivity in Intelligent Tutoring Systems" *The 18th International Conference on Artificial Intelligence (ICAI'16),* USA, 2016. [Accepted]

- Ankita Juneja and Harkiran Kaur, "Analyzing Learner's Cognitive abilities to predict the learning outcomes in an Intelligent Tutoring System",Ninth International Conference on Contemporary Computing(IC3), 2016. [Communicated]

VIDEO LINK

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