

Enhanced Student Support System in Open and Distance Education Using Long Short-Term Memory Recurrent Neural Network

*¹Fergus U. Onu, ²Christiana U. Ezeanya, ¹Ikechukwu Ezea and ³Omo-Okhirelen Obabueki

¹Department of Computer Science, Ebonyi State University, Abakaliki, Nigeria

²Directorate of ICT, National Open University of Nigeria, Enugu Study Centre, Nigeria

³Department of Computer Science, Lagos State University of Science and Technology, Ikorodu, Nigeria
{uche.fergus@iykeezee@gmail.com|cezeanya@noun.edu.ng}

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ORIGINAL RESEARCH

Abstract- Open and distance education provides access to education to all categories of learners. Learners in Open and Distance education system face the problem of inadequate support services especially when they encounter issues on their studies that need urgent attention. The educational services offered in open and distance education system can only be effective if there is an effective student support system. This study explores the need to enhance the open and distance student support system using Long Short Term Memory neural network. The approach of machine learning was adopted in the area of issue and complaint resolution whereby the issues/complaints are raised in the form of a ticket which is categorized based on their priority. The Last Short Term Memory neural network was used in the prediction of the best solution based on previous input. The enhance student support system was able to provide effective and timely feedback on student issues and complaints. This in turn lowers the rate of student dropout from the system and also provides enabling learning environment for the learners. Machine learning-based student support services improve the effectiveness of the service rendered thereby making the learners improve their academic performance.

Keywords- Key Performance Indicator, LSTM, Recurrent Neural Network, Tutor Marked Assignment

1 INTRODUCTION

Open and Distance education system plays important role in the society as it allows the society especially those that have need to acquire education to do so. It offers education to the door step of every individual who has the urge to acquire education with no barrier to distance, gender and age. The advent of covid-19 pandemic advanced the adoption of technological tools in the education system to improve on the service delivery (Mensah *et al.*, 2020).

The Open and distance education system has witnessed the increase in student enrolment especially the working-class individual who wants to improve their skill and knowledge in their professions (Musingafi *et al.*, 2015; Gurhan & Sarkin, 2020). This individual has the challenge of combining study with their work schedule and family which in turn becomes too tedious for them thereby making support system important. Student support system plays an important role and it is a vital ingredient in open and distance education because it offers student support to learners who are in need of the support from the start of the application to study a program to the completion of the program. To address the challenges of poor feedback and delayed response to students' issue, there is need for an effective support system. Currently machine learning based system is being used in education system to enhance educational processes (Kotsiantis, 2011).

One of the key elements in ensuring the quality of education is a support system. It promotes the diversity of students' experiences and lowers the dropout rate (Alina, 2013). A strong support network reduces the loneliness of learners which is one of the disadvantages associated with ODL (Maxwell *et al.*, 2015). Some of them that cannot cope with challenges tend to drop out of school. The application of machine learning to the student support service especially in the area of tackling the issues and complaint will enhance the effectiveness of the services as well as making the study environment conducive for the learners.

2 LITERATURE REVIEW

2.1 STUDENT SUPPORT SERVICES

When referring to student support services, we mean those services that are given to students to enhance their learning environment. Student services were also described by Stewart *et al.* (2013) as the academic and non-academic policies and procedures that support and help students' academic performance.

Support services in open and distance learning have received the majority of study attention since they are the main factor influencing student dropout rate. Support services are significant component that makes the system efficient and long-lasting according to Kamtepe *et al.* (2018). It bridges the gap between the management and the learners, especially when the latter are alienated and feel out of place. In a distance and open learning institution, support services are crucial. Giving students a sense of belonging and encouraging them to finish their program is ODL's service component. The practice of distance learning has evolved into an educational model that integrates students into their learning environment and promotes communication among the stakeholders. According to

*Corresponding Author

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Farajollahi and Moenikia (2010), a distance education system's ability to provide acceptable support services, which in turn foster a feeling of community among students, is highly dependent on the effectiveness of the support services.

The quality and effectiveness of the support provided to distance learners significantly influences the success of distant learning. Responding to the high rate of issues and complaints emanating from distance learners according to Zuhairi et al. (2019), becomes the biggest issues facing open and distance learning education. We can see that support services put a lot of emphasis on students and the learning environment, particularly where there is distance barrier between the learners and the educational institutions (Kumtepe et al, 2019).

The Africa Centre for Distance Education (ACDE) said in the policy framework and best practices that structures and procedures for giving the students timely feedback are necessary for ODL to have enduring quality. The availability of information and technology resources independent learner has an effect on the learner support services in both traditional and distance learning institutions. In fact, support services today encompass system stakeholders in addition to learners as a result of technological improvements (Kumtepe et al, 2019).

Arfin (2018) looks into how student support services might raise students' endurance at Indonesia's Open University. The following justifications were cited as reasons why students couldn't continue with Open University study. The study centre and regional offices' dearth of academic and non-academic support is one of the contributing reasons. These supports include academic and non-academic services. He asserted that establishing a productive learning environment and an appropriate response system in the system for student support will greatly boost students' persistence in open and distance learning. Effective support services are required in order for learners to successfully complete their studies by striking a balance between their studies and other duties. Technology advancements have necessitated a significant shift in how technology is used in teaching and learning. Support systems that encourage quick responses and enhance information flow are now crucial. Stelwart et al. (2013)

2.2 COMPONENTS OF STUDENT SUPPORT SERVICES

Students require assistance in order to manage their difficulties, reduce the dropout rate, and successfully adjust to the unique demands of distance learning. The six important components listed below serve as a crucial outline to be considered when creating a student support system (Stelwart et al, 2013).

- i. Learners' attribute,
- ii. Program specifications,
- iii. Location,
- iv. Technology,
- v. Scalability, and
- vi. Management systems

Learners' attributes are frequently needed to emphasize that they are important factor in the improvement of a

student support system (Stewart, 2013). One of the attributes in the aspects of the methods to teaching and learning is client or customer centeredness. One of the most challenging issues in open and distance education is how to meet the exceptionally high expectations of learners and organizations. Finding the technologies ideal for students and the institutions as a whole when choosing student assistance services technology can be challenging. A course or program rises to the top of the list of student support services because of its uniqueness.

The settings of the school and its students have a significant impact on how support services are provided. Students from various geographic locations can access the educational skills they want to learn in an ICT-driven environment. Some significant threats need to be addressed in the management of student support programs. Hierarchical can be both beneficial and detrimental in a centre-periphery model. The capabilities provided by the environment of information technologies may be specifically helpful in the effort to create a coordinated learning environmental model. Secondly, in order to offer students high-quality services that are both effective and efficient, information management and administration are essential. Using information management, it is possible to monitor students' progress and allocate resources to support them. Determining how successfully services are being given will depend heavily on the information gathered. The transfer of information among outlying components is a vital component of total knowledge management, and updating this knowledge is a major duty for both centre and the periphery.

2.3 MACHINE LEARNING

Making a system learn from a series of events in order to anticipate the next occurrence is known as machine learning (Kotsiantis, 2017). Two steps are used to generate the classifier. First is to build a classifier model from an existing dataset. This process, which is also known as training, involves the construction of classification rules. The accuracy of the classification criteria is evaluated in the second stage, which is known as the testing step. Only in cases when the classifier's accuracy exceeds the required threshold will the classifier model developed in the initial phase be used to classify the newly discovered data records.

In order to train classifiers, machine learning algorithms are required, and selecting the best algorithms becomes important since it affects the accuracy of the predictions. Many scholars have employed machine learning methods for classification over the years in a number of different knowledge fields. Each machine learning activity requires a unique combination of algorithms that look for patterns to carry out specific tasks. Therefore, using mathematical tools to input data, machine learning learns from that data before analysing it to carry out a function. Building models that will learn to distinguish between trends in order to generate the desired outcome is the main goal of machine learning. These models are created using a variety of algorithms and internal procedures.

2.3.1 Machine Learning Techniques

The first method is supervised learning, which converts input into an output using examples of input-output pairs. It is implemented when the goal is recognized using the set input and employs a labelled training data set. When data indicates that an event is likely to occur and that the input has knowledge of the desired outcome, supervised learning is applied. An assortment of inputs and their similar outputs are used by the algorithm to learn. It compares the input and the output during the process to look for errors, and when it does, it adjusts the model. When combined with supervised learning, classification effectively predicts the outcome from the input. It functions somewhat by classifying unknown groups of items into bigger recognized groups.

Unsupervised Learning employs unlabelled data sets with no human intervention. For generative feature extraction, trend and structure identification, result grouping, and exploratory purposes, it is commonly utilized. Examples of tasks include identifying association rules, anomaly detection, feature learning, density estimation, and clustering. It works best when data is grouped into sets of related data during clustering.

Semi-Supervised is a methodology which incorporates both labelled and unlabelled data sets, merges both unsupervised and the supervised methodologies. This suggests it is capable of learning both under supervision and independently. A semi-supervised technique's main advantage is its improved ability to predict labelled or unlabelled data. Some uses include test categorization, fraud detection, data labelling, and machine translation.

Reinforcement technique is also known as an "environment-driven approach". It enables software agents and robots to automatically assess the best course of action based on their surroundings or context (Sarker, 2021). This technique of learning involves using characteristics learned previously to raise the reward or lower the risk.

2.4 ARTIFICIAL NEURAL NETWORKS

Deep learning using artificial intelligence is a component of artificial neural networks. The interconnected human brains that represent neurons are used to carry out a certain task. It is used to simulate how people would respond in complicated situations in order to address production problems. Deep learning, speech recognition, data prediction, and other applications benefit from its optimal utilization. Artificial neural networks are made up of numerous layers of connected artificial neurons that are activated by various functions to carry out certain tasks.

The neuron can be turned ON or OFF with the use of an activation function represented by a mathematical formula. It consists of three layers:

- i. An input layer that displays a vector's dimension

- ii. A hidden layer that uses activation functions to convert input into output.
- iii. Output layer, which is the neural network's result.

The concept of neural networks, according to Larose (2013), emerged from the understanding that the intricate learning processes carried out by the human brain are composed of networks of closely connected neuronal clusters. ANNs have a large number of parameters, which gives them a great deal of flexibility and allows them to correctly mimic issues with very simple functions. The remarkable tolerance of neural networks to noisy data is one benefit. Additionally, training timeframes for neural networks can take anywhere from several hours to several days, which is longer than it does for decision trees.

2.4.1 Long Short-Term Memory (LSTM)

The LSTM is a recurrent neural network (RNN) that may learn long-term dependencies for issues involving sequence prediction. In addition to processing single data points like images, the response linkages in LSTM allow it to analyse the whole data sequence. Its feature of internal memory which helps in remembering critical things about the input allow it to predict what the next occurrence will be. This is the reason why it is preferred algorithm for sequential data. LSTM is an extension of RNN that contains information that enables it to remember inputs over a long period of time. LSTM solves the problem of vanishing gradient which is the issues in RNN.

In LSTMs gates determine the information to be added or deleted from the cell state. These gates permit information in and out of the cell. The sigmoid neural network layer and point-wise multiplication operation help the mechanism. The state of the sigmoid layer determines the output. If it is output "Zero", it indicates that nothing should be let through and if one, it indicates everything should be let through. LSTM remembers all the past knowledge up till the present point while it forgets unnecessary materials. To do this, many "gates," or activation function layers, are introduced. Each LSTM recurrent unit additionally takes account of a vector known as the Internal Cell State that theoretically describes the data which was chosen to be kept by the prior LSTM recurrent unit. A long short term memory network is composed of four different gates, each performing a particular purpose. These gates are as follows: -

1. Gate (f) of Forget decides how much of the past data should be deleted.
2. The input gate I: It regulates the information that will be written to the internal cell state.
3. Gate (g) for Input Modulation In a lot of LSTM literature, it is assumed to be in the input gate because it is consistently seen as an element of the input gate. The internal state cell's information is written by the input gate with zero-mean and nonlinearity thanks to the input modulation. In order to reduce learning time, zero-mean input is used because it has a faster convergence rate. Despite the fact that the activities of this gates are less crucial than others, they are sometimes viewed as a finesse-

providing idea, that is why it is advisable to include this input modulation gate at the structure of the LSTM unit.

4. The output gate determines what output (next Hidden State) should be produced from the internal cell state that is now in place.

2.5 THE SUPPORT SYSTEM ARCHITECTURE

The steps taken to construct a solution in the machine learning support system are shown in Figure 1. The strategy, which has four basic components and makes use of several data processing methods, is shown in Figure 1. The data is subjected to a fundamental Feature

Engineering procedure before moving on to the main processes. After completing this pre-processing, the series of actions that make up our strategy are started. Following the completion of each of the key processes, a model is developed and assessed using machine learning algorithms according to the current state of the dataset for each scenario.

In accordance with the issues being taken into consideration by the ticket, this technique allows us to receive a list of solutions at the end of the process from which we can evaluate and select the best answer from.

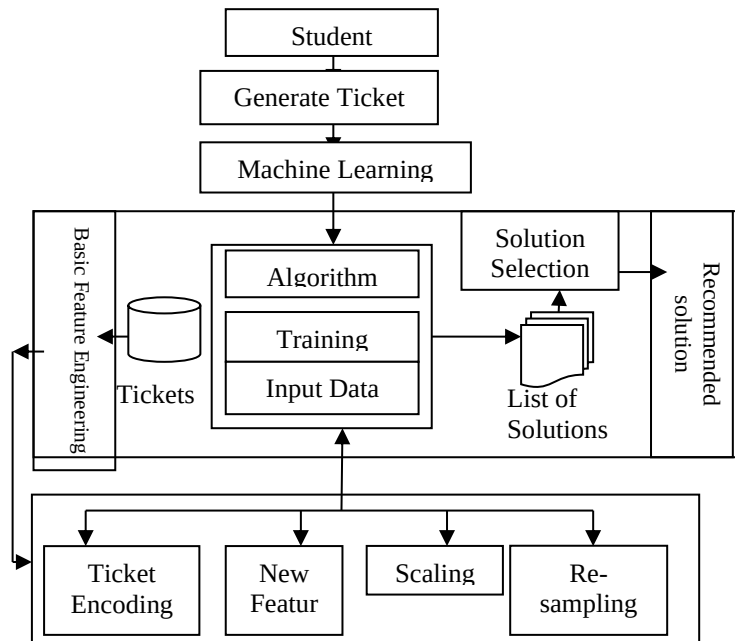


Fig. 1: Architecture of the machine learning support system

The summary of the steps involved in the machine learning system represented in the figure 1 above are:

- i. Collecting data issues and complain from the user in the form of ticket.
- ii. Analysing the input data.
- iii. Providing solution from the already existing solution from the trained data in the model
- iv. If there are no similar keywords, the issue is sent to the support team, when the solution is provided, the model is trained and stored in its database. The model provides the solution in the next similar issues inputted

3 METHODOLOGY USED AND RESULTS OBTAINED

Object Oriented Analysis and Design Methodology (OOADM) approach was used in analysing and building the new system while the long short term memory neural network was the machine learning techniques used in categorizing the ticket and also providing quick response to issues or complaints that needed urgent response.

3.1 ARCHITECTURE OF LSTM

Four neural networks, often known as cells, and separate memory building elements make up the structure of the LSTM as shown in Fig. 2;

The cell state is indicated by the horizontal line that runs vertically through the top of the diagram in fig. 2. It is comparable to a conveyor belt through which information simply and unaltered passes. The gated cell is seen as the memory and this cell decides when to store or delete information. It decides which information is important and the one to discard. It consists of 3 gates; the input gates, forget gates and the output gates. These gates are controlled by sigmoid using 0's and 1's as open and close. These three gates regulate information flow, which is used to forecast output of the system.

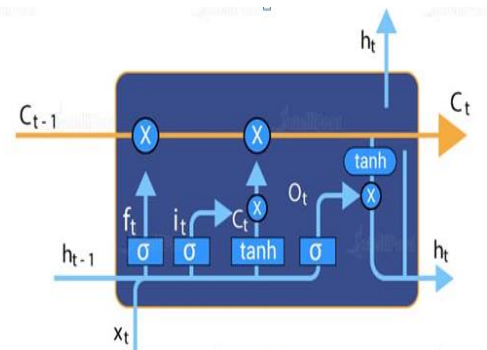


Fig 2: Architecture of LSTM (Intellipaat, 2022)

Input gate: The input gate changes the cell state to include important information. The inputs h_{t-1} and x_t are used to control the data first using the sigmoid function, which selects the values that need to be recalled in a manner similar to the forget gate. The tanh function is then used to produce a vector containing all of the potential values from h_{t-1} and x_t , with an output range of -1 to +1. The useful information is finally obtained by multiplying the vector's values by the controlled values. This is shown in Fig. 3.

$$i_t = \sigma(w_i [h_{t-1}, x_t] + b_i)$$

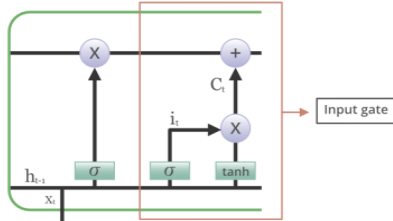


Fig. 3: Input gate (Aakarsha, 2021)

Forget Gate: The forget gate, as depicted in fig. 4, eliminates data that is no longer useful in the state of the cell. The gate gets new types of input data: x_t (input at the present time) and h_{t-1} (output from the previous cell). These data are multiplied with weight matrices and added to with bias before being fed into the gate. An activation function is used to output the result as a binary value. If the result for a particular cell state is 0, data is lost, but if the result is 1, data is retained for use later. This is shown in Fig. 4.

$$f_t = \sigma(w_f [h_{t-1}, x_t] + b_f)$$

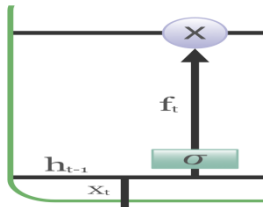


Fig. 4: Forget gate (Aakarsha, 2021)

Output gate: The function of the output gate, as depicted in fig. 5, is to extract useful data from the present cell state and release it. The cell is initially utilized to construct a vector using the tanh function. The information is then regulated by the sigmoid function after being filtered by the values to be remembered using the variables h_{t-1} and x_t . Lastly, the values of the vector and the regulated values are multiplied and delivered, accordingly, as input and output to the succeeding cell. This is shown in Fig. 5.

$$o_t = \sigma(w_o [h_{t-1}, x_t] + b_o)$$

Where,

$i_t \rightarrow$ represents input gate.

$f_t \rightarrow$ represents forget gate.

$o_t \rightarrow$ represents output gate.

$\sigma_t \rightarrow$ represents the sigmoid function.

$w_x \rightarrow$ weight for the respective gate(x)neurons

$h_{t-1} \rightarrow$ output of previous LSTM block at time $t - 1$

$x_t \rightarrow$ represents input at current timestamp.

$b_x \rightarrow$ biases for respective gates(x)

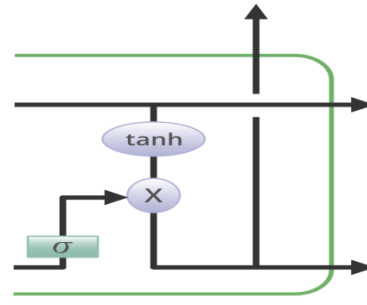


Fig. 5: Output gate (Aakarsha, 2021)

4 RESULTS AND FINDINGS

4.1 NUMBER OF TICKETS GENERATED

The total number of opened tickets throughout the course of a particular period of time can be determined using this KPI. For instance, fig 3 display the number of tickets opened per month from during the test period June 2022 through July 2022. Accordingly, there were 1500 total tickets entered into the system at that time.

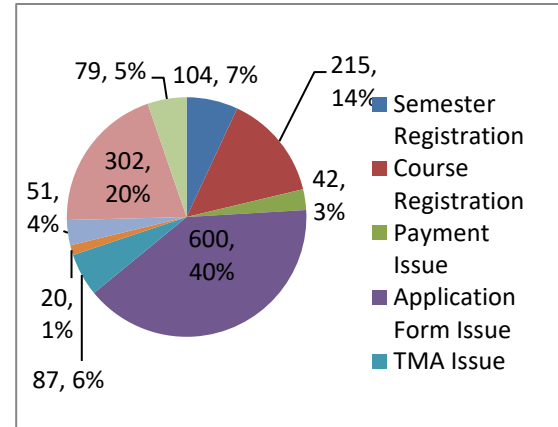


Fig. 6: Total number of tickets sent throughout the testing period

The total number of tickets opened throughout the system testing period is shown in Fig. 6. It is clear that 5% (or 79) of the support tickets submitted by students have issues with entrance requirements. 20% (302) of the tickets were related to semester outcome problems. Transcript problems account for 4% (51 tickets), exam problems for %1 (20 tickets), TMA problems for 6% (87 tickets), admission application problems for 40% (600 tickets), payment problems for 3% (42) tickets, course registration problems for 14% (215 tickets), and semester registration problems for 7% (104) tickets.

4.2 NUMBER OF TICKETS RESPONDED TO

The total number of tickets handled within a specified time period is calculated using this KPI. Figure 7 show the number of responses for the system tickets sent over the timeframe.

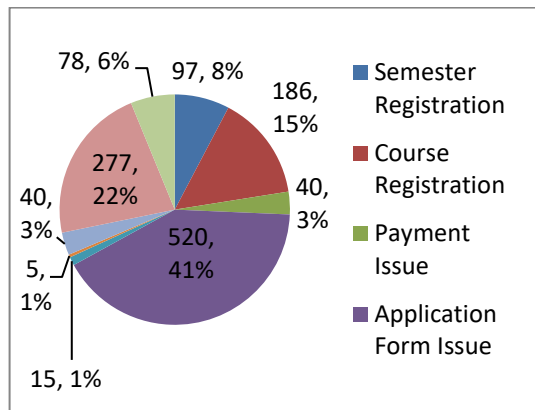


Fig. 7: Total number of tickets handled within the specified period

Fig. 7 shows that 6% (78) of the support tickets submitted by the student regarding a problem that would have required admittance received a response. 22% (277) of the tickets submitted regarding semester outcome concerns received a response. The following tickets received a response: 3% (40) tickets regarding transcript issues, %1 (5) ticket regarding exam issues, 1% (15) tickets regarding TMA issues, 41% (520) tickets regarding admission application issues, 3% (40) tickets regarding payment issues, 15% (186) tickets regarding course registration issues, and 8% (97) tickets regarding semester registration issues.

4.3 PERCENTAGE OF TICKETS NOT RESPONDED TO

With the help of this KPI, you can determine the proportion of tickets that went unanswered over a given timeframe and the cause of it. Fig. 8 displays the percentage of tickets that the system did not resolve within the specified time frame.

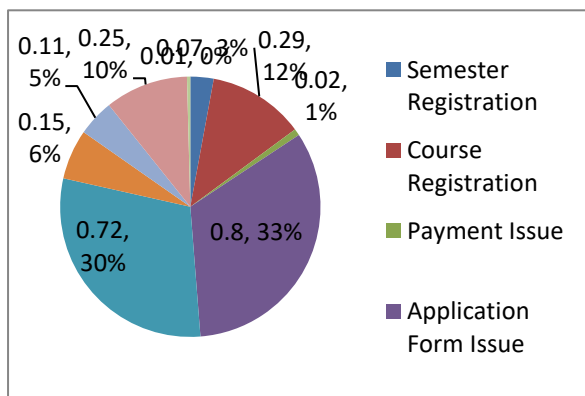


Fig. 8: Percentage of tickets not responded to during selected period

Fig 8 shows that the biggest percentages of unanswered tickets are related to Application difficulties (22%) and TMA issues (30%). Given that the time in question is for registration, this is due to the low priority given to this category of tickets.

4.4 AVERAGE RESPONDED TICKET TIME

The typical ticket response time throughout the course of a chosen timeframe is determined by this KPI. The percentage of tickets in the system that received no response within the specified time is shown Fig. 9, which indicates that the average ticket response time for

application form and TMA issues is long; 15 minutes on average.

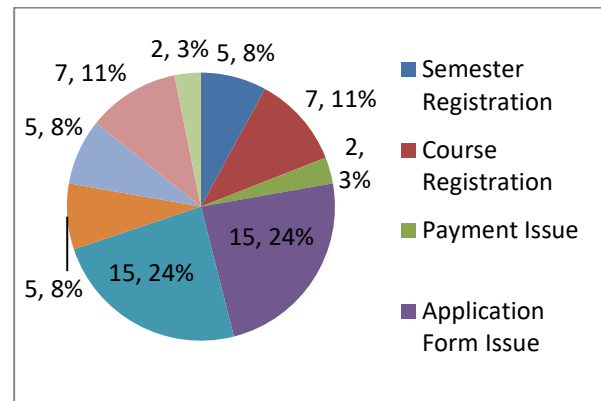


Fig. 9: Average Responded Ticket Time

4.5 CLASSIFICATION ACCURACY

The accuracy of tickets' categorization into their respective categories is determined by this KPI. The effectiveness of the software was evaluated using the accuracy rate of tickets based on its categories. As shown in table 1 and equation 5.1, a performance metric that shows the accuracy (AC) of the machine learning algorithm may be generated from the confusion matrix.

Table 1. Observed Confusion Matrix

	True		False
	True	TP	FP
Predicted	False	FN	TN

$$AC = \frac{a + d}{a + b + c + d}$$

- a = True Positive
- b = False Positive
- c = False Negative
- d = True Negative

1500 tickets were categorized on the system throughout testing to determine its accuracy in determining the ticket category.

Table 2. Observed Confusion matrix applied to test dataset

	True		False
	True	1498	0
Forecast Route	False	0	2

Table 2 demonstrates that 1498 of the 1500 tickets available are True Positive and were correctly anticipated. Two was thought to be a False Negative (it displays the incorrect categorization, but it is not). Finally, a model of performance metrics that illustrates the correctness of the system can be generated from the confusion matrix. Substituting values, we have

$$AC = (1498 + 0) / (1498 + 0 + 0 + 2)$$

Accuracy in estimating the ticket category is 99.8%.

Table 3. Performance Results Attained

Technique Applied	Accuracy in ticket classification
LSTM RNN	99.8%

5 CONCLUSION

The main purpose of this research is to provide an effective student support system for open and distance learners. Open and distance education gives flexibility in learning but at the same time isolate learners from each other. Learners of open and distance education system are often faced with the challenges of resolving issues that arises at the course of their studies due to distance barrier. Providing timely response to these issues boost the morale of these learners. The new system will help to enhance the performance current student support services been rendered in most ODL system. Shikulo & Lekhetho (2020) established the fact that high rate of learners' dropout in ODL system is attributed to lack of adequate student support services which he recommended addition of more counsellors.

Due to the fact that ODL system is characterized by large population, the support team or counsellors will always be overwhelmed by the number of issues or complaint that will be assigned to them each day. The enhanced student system using long short term memory neural network in solving students' issues or cases has proven to be an effective way of resolving issues. From the observed confusion matrix table, it was observed that 98% of the tickets or issues raised were anticipated correctly. The system was able to respond to issues that it has learnt its solution based on the previous solution provided by the support team. This gives timely response and feedback to learners making them motivated towards their learning process.

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