Enhancing Accuracy of Chatbot with Optimizers and Deep Learning Algorithms

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***Abstract*—In the recent era, chatbot is widely used in almost all the day to day applications. Chatbot, as the name indicates, is a robot involved in chat ,which is why the name chatbot. A bot whose main focus is chat, but when we say so, it is very important that the responses given as a reply to a query asked by the end user be right. People trust only a chatbot whose accuracy in terms of right responses is high or which is almost close to right answer. When we design a chatbot the concern arises as to which techniques or algorithms to use when fed with an input which will make chatbot give correct and best response so that the end user builds his/her trust over the chatbot. Deep learning computation to measure performance for a chatbot is demonstrated in this work. Optimizers used in this paper include Adam, RMSprop and SGD. Algorithms include LSTM, GRU and Simple RNN where Simple RNN with optimizer Adam achieved highest accuracy of 99.51% with epoch and batch size set to 50 and 16 respectively.**

***Index Terms*—Chatbot, Deep Neural Network, Optimizers, Trustworthiness, Accuracy.**

I. Introduction

CHATBOT is part and parcel of almost all AI applications used today on a daily basis, which cannot be ignored. For instance, on opening a school/college website along with various information we could see, quickly there pops a small window saying Hi, how can I help you. Where the intension of the website owner is to make his/her end-user job easier and he/she is comfortable and satisfied using the website or application. The expectation is that the information the user wants is easily available to him/her and also the information received should be right to his knowledge. If the information availed on the website is limited, then the need of a chatbot becomes obsolete. But, for instance, a banking website where a lot of information and actions required. A user who is new to the website might find the urgency of assistance. This guidance or support could be provided by a chatbot. At present queries can be raised to a chatbot via text or voice messages, irrespective of the medium of communication chosen, expected outcome must be getting the right answer for his/her query and at the earliest. ChatGPT [32] generative AI is used in the field of education by students [1] for their day-to-day studies. With the release of Open AI's ChatGPT Large Language Models (LLM) raised higher standards in AI industry [25]. Banking, insurance, and healthcare are application areas where the chatbot is expected to respond appropriately. Otherwise,it can cause enormous irreplaceable financial and human health loss. The organization that designs an authenticated website provides a chatbot service. Users using the chatbot, trust [2] [35], completely if the chatbot fails, trust in the organization deteriorates [3] [18]. The need for a chatbot to provide accurate information and guidance to stakeholders arises [5].

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II. Background Study

Chatbot generally could be implemented using techniques like NLP, Pattern Matching, Naïve Bayes Algorithm, Sequence to sequence encoder, Hybrid Emotion Interface Model (HEIM), Long Short-term Memory (LSTM). The paper concludes LSTM gives better result than simple RNN. HEIM algorithm is best for real world data sets to interpret human emotions [6]. Another article using Cornell Movie Dialog Corpus, Indicates although there are many other models that may be used for chatbot applications in Python programs, When the LSTM model is applied to the chatbot software, the output results include accuracy [9][37]. NLP can be used for a chatbot where predefined knowledge is used as a base for user's queries. NLP enables the chatbot to take in input, deconstruct it, comprehend it, choose the best course of action, and respond in language instinctive for the user. NLP also carries out task domain and mapping and may be applied to input semantic analysis as specified in this paper [7]. In a research, machine learning algorithms like K-nearest neighbor (K-NN), Support vector machine (SVM), Naive bayes (NB), Decision tree (DT), and Random Forest (RF) are used to analyze gathered data. Study findings conclude SVM performs the best among these algorithms [11]. Machines learning neural networks algorithms such as Recurrent neural networks (RNNs), Convolutional neural networks (CNNs), and Generative adversarial networks (GANs), have shown assuring results in improving performance of chatbot. Particularly, RNN has demonstrated strong qualities in sequence modelling and task for dialogue generation. Additionally, meta-analysis through an article findings indicates machine learning algorithms varies respectively depending on the dataset used and chatbot application in particular [12]. Another neural network algorithm called Bidirectional Recurrent Neural Networks (BRNN) with attention layers are used to respond with more relevant dialogue to input sentences with a lot of tokens, or sentences longer than 20–40 words. The primary goal of this work is to find Bleu by increasing the model's complexity and learning rate [8]. Along with choice of algorithms, selection of optimizer is considered to be one of the most crucial steps in functionality improvement of chatbots using neural networks. Optimizers mainly regulate the modification of model parameters like weight and bias, to minimize a loss function during training. ADAM, SGD and ADAMW are some of the well-known optimizers. When generalization and training efficiency are the main issues, ADAMW is a viable substitute as per this article [10]. For Amazon Alexa Prize contest a deep reinforcement learning chatbot MILABOT was created. It can communicate with people on well-known small topics both orally and in writing. When assessed through A/B testing it was observed, system functions noticeably better than several rival solutions [13]. A comparison is made between the Manhattan, Canberra, Euclidean, cosine, Jaccard, dice, and Chebyshev similarity approaches for a student admission Chatbot with retrieval-model notion. The Dice- and Cosine-Samaphore Approaches were identified to be the most successful on the basis of the test results. Reliable outcomes were obtained 75% of the time. Dice and cosine similarity obtained a f1-score above 80% on all investigated thresholds. Recall yields incredibly good outcomes, such as 100%[14].

III. Chatbot Family

Fig. 1. depicts the various members of the chatbot family developed by researchers and programming experts. Depending on various factors such as application fields [19], user requirements [15] etc. Categorization of chatbot includes menu driven, rule based, NLP based, ML based, Hybrid and voice based chatbot.

Menu driven chatbot: The answers for the user's query is displayed in terms of menu, once clicked on one of the options from the menu, user will be redirected to next set of option, until user is satisfied with the response. This method allows the user to choose the best option that is suitable for their scenario [17]

Rule-based chatbot: This method follows the keyword or phrase matching technique in order to respond to the user's query. If the phrase or word user mentioned in the query is present in the chatbot database, the corresponding response is provided as an answer. The synonym of the word can also be considered to answer questions.

NLP based Chatbot: Natural Language Processing (NLP) answers the query by observing the intent of the user before providing the response. Human language understanding is the key used in this type, rather than only keyword matching as in rule-based chatbot [20].

Machine Learning (ML) based chatbot: These chatbot remembers conversations between the users using AI techniques; if the same user tries to converse back, chatbot could ask whether the same preferences they want to use already used before.

Hybrid chatbot: Chatbot of this kind is a combination of two chatbot types AI based and rule based chatbot, and provides better results comparatively based on application for which it is been used.

Voice chatbot: It is a type of conversational AI that uses text-to-speech and speech-to-text functions to understand user queries. Could be helpful to people who are physically impaired in typing the query, still can make use of chatbots to complete their job [20].

IV. Chatbot Implementation Methods

Chatbot could be implemented using various methods such as:

1. Natural Language Processing (NLP): It is the process in which the chatbot tries to understand what query the user has typed, breaks the query into parts, extracts meaning from each part, responds to the user using natural language. Chatbot to comprehend and act upon unstructured data, Natural Language Understanding (NLU) transforms it into structured data. NLU focuses on deriving meaning from queries entered by users. Natural language generation (NLG) merely translates the structured data response produced by the chatbot into natural language that is comprehensible to humans [2] [34].

2. Deep Learning Models: Chatbot can be implemented using Deep learning models. Currently, employing artificial neural networks to build chatbots is common. However, teaching a computer to have genuine conversations is quite challenging and frequently requires vast and complex language models.

3. Generative Artificial Intelligence: An AI chatbot, sometimes referred to as an AI writer, is a kind of AI-powered application that can produce written text in response to human input. When a user requests it, AI chatbots may compose anything from an essay to a rap song. Each chatbot's capabilities, such as whether it is linked to a search engine, determine how much it may write about. LLMs are used by chatbots to train AI to respond in a manner similar to that of a human. Although some programs rely only on the data they were trained on, others include Web connectivity, giving them access to the most recent information [4].

V. Proposed Model

A. *Deep Neural Network Algorithms*

The proposed model shown in Fig. 2. uses mainly three deep neural network algorithms for experimentation in this paper [21] [33]: 1. Simple RNN (Recurrent Neural Networks): To retain knowledge from previous inputs, recurrent neural networks use a method in which the output from one stage is given as input to the next. Because of this nature, RNNs are considered best for predicting the next word given a phrase, where the context of previous steps is crucial. RNNs are distinguished by their hidden state, sometimes referred to as the memory state, which retrieves important data from previous inputs in the sequence. Compared to conventional neural networks, RNNs perform consistently across inputs , using the same parameters in every phase, thus lowering the complexity of the parameters . This characteristic indicates that in sequential tasks RNNs are very good [23].

2. LSTM: Long Short-Term Memory, or LSTM for short, is an artificial recurrent neural network. An extension of recurrent neural networks (RNNs), Primarily LSTM networks were developed to handle situations in which RNNs are ineffective. It is not possible to retain the data for an extended period of time. To forecast the present output, it is necessary to go through particular data saved in the past sometime prior. However, RNNs cannot manage these 'long-term dependencies' at all. It is impossible to precisely specify the amount of past data that should be 'forgotten' and the amount of data that should be 'preserved'. The primary function of LSTM in chatbots is voice recognition. The LSTM algorithm works best for processing, classifying methods, and generating predictions from time series data [22][37].

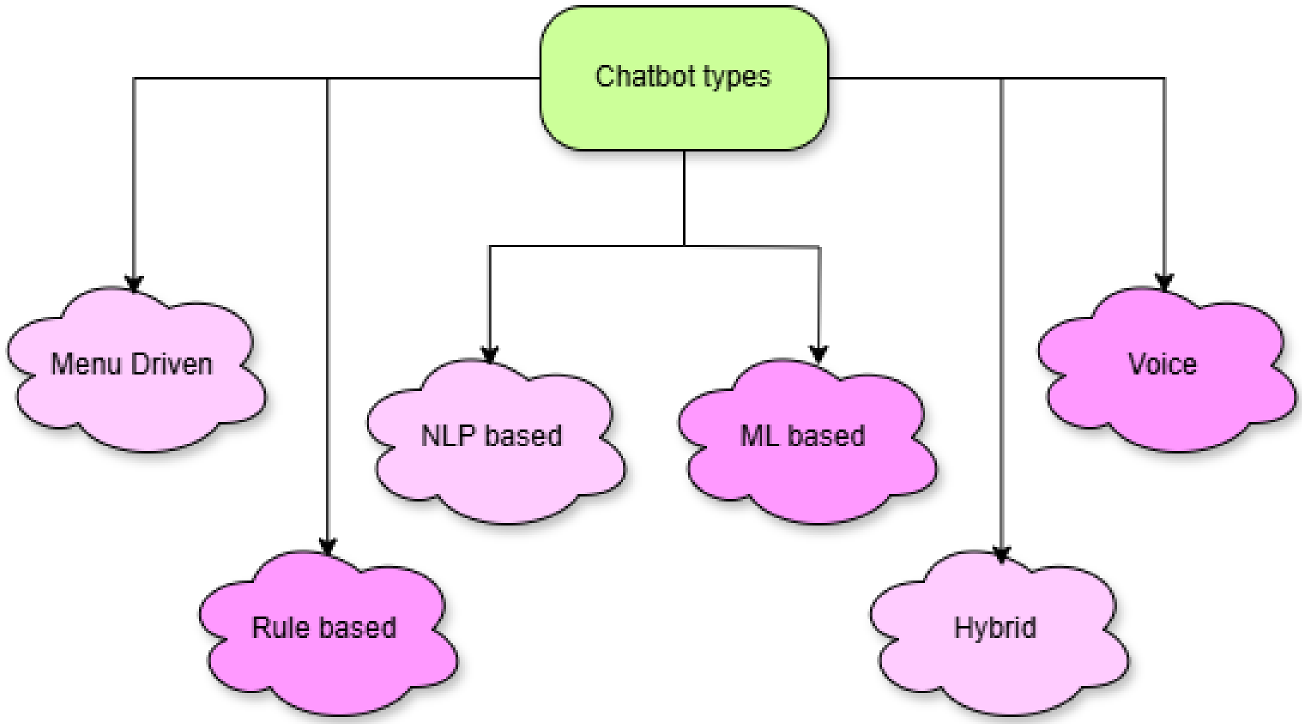

Fig. 1. Types of Chatbot

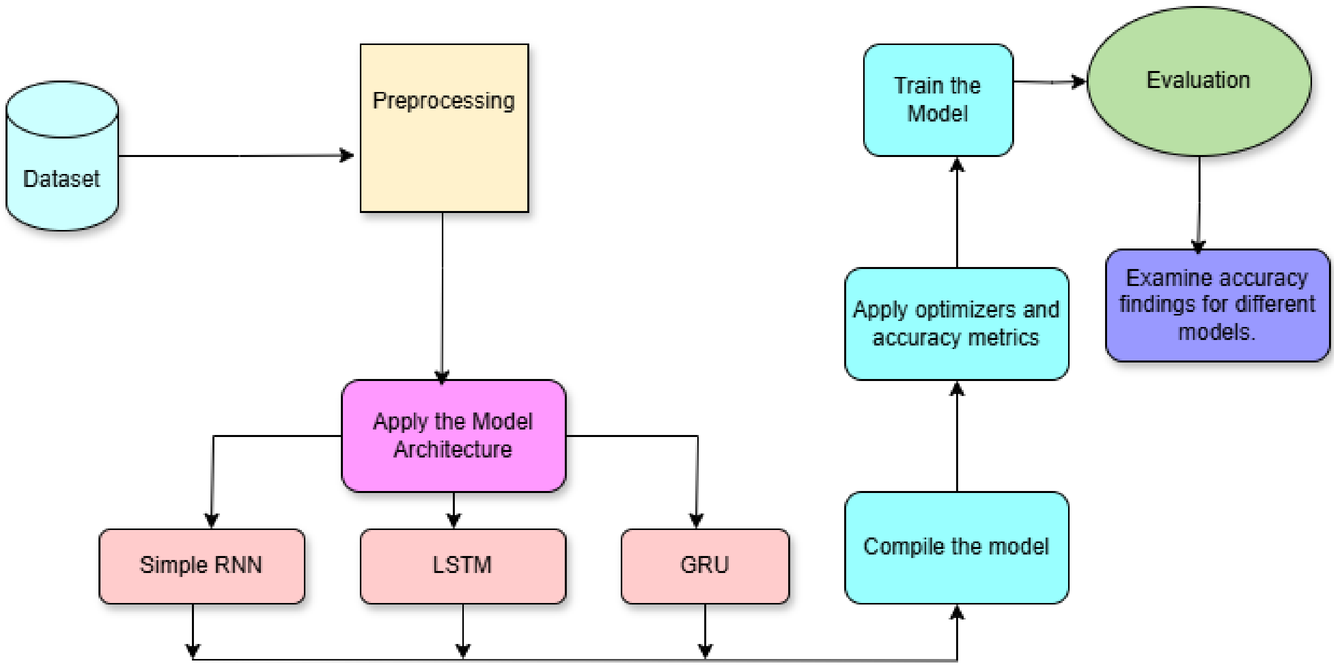

Fig. 2. Flow Diagram of Proposed Model

3. Gated Recurrent Unit (GRU): Is a type of RNN. GRU's fundamental concept is to revise network's hidden state selectively at each time step by using gating methods. Information coming in and out of the network is handled by the gating mechanisms. GRU owns two gating mechanisms that reset and update the gate. While the update gate decides the amount of new input needed to update the hidden state, the reset gate decides on amount of prior hidden state needed to be forgotten. GRU's output is calculated using the updated hidden state [24].

B. Optimizers

The proposed work uses three optimizers to generate accurate predictions by reducing the loss function and maximize efficiency 1. Adam: Adaptive Moment Estimation, Adam Optimizer is a well-liked optimization technique for deep learning model training. It combines the benefits of RMSProp and AdaGrad, two more additions to stochastic gradient descents. Adam keeps a different learning rate for every parameter and modifies it as he learns more. Using estimations of first and second moments of the gradients, it calculates different adaptive learning rates for various parameters [26]. 2. RMSprop: An adaptive learning rate optimization technique called RMSprop (Root Mean Squared Propagation) was created to boost neural network training effectiveness and performance. By modifying the learning rate for every parameter according to the historical gradients, it seeks to overcome the shortcomings of the Adaptive Gradient Algorithm (AdaGrad). The gradient is divided by the root of the moving average of the squared gradients, which is maintained by RMSprop. This keeps the learning rate from falling too low and helps normalize the gradient [26]. 3. SGD: An iterative optimization technique called stochastic gradient descent (SGD) modifies model parameters according to the loss function gradient to minimize an objective function. SGD [10] is computationally efficient for large datasets because it uses a single random sample or a small batch of samples for each iteration, whereas traditional gradient descent, computes the gradient using the entire dataset.

C. Dataset

The University Dataset is used in this research which comprises of 38 intents as shown in TABLE I. Every intent comprises of set of responses [27].

TABLE I
INTENTS LIST

Sl. No	Intents	Sl. No	Intents
1	greeting	20	ithod
2	Goodbye	21	computerhod
3	Creator	22	exthod
4	Name	23	principal
5	Hours	24	sem
6	Number	25	admission
7	Course	26	Scholarship
8	Fees	27	facilities
9	location	28	College intake
10	Hostel	29	Uniform
11	event	30	committee
12	document	31	random
13	floors	32	swear
14	syllabus	33	vacation
15	library	34	sports
16	infrastructure	35	salutation
17	canteen	36	task
18	Menu	37	ragging
19	Placement	38	hod

D. Chatbot Evaluation Metrics

Chatbot can be evaluated using following metrics:
1. Mean Squared Error (MSE)
2. Area Under the Receiver Operating Characteristic curve(AUC-ROC)
3. Confusion Matrix: Shows how well model performs by predicting correct and incorrect predictions
a) Accuracy:
  i) Accuracy class
  ii) Binary Accuracy class
  iii) Categorical Accuracy class
b) F1 score
c) Precision

VI. Results and Discussion

The study focuses on neural network algorithms Simple RNN, LSTM and GRU, whose accuracy is examined with popular optimizers Adam, RMSprop and SGD. Each algorithm is evaluated for Accuracy metrics like Accuracy, Binary Accuracy, categorical accuracy and Regression Accuracy metric MSE and classification metric like AUC, Precision and F1 score. When implemented with a validation split of 80:20 (80When epoch size is set to 50 and batch size is set to 16 respectively with different optimizers and accuracy metrics the Accuracy obtained are shown in table and graphs below for algorithms LSTM, Simple RNN and GRU for three optimizers Adam, RMSprop and SGD. TABLE II depicts LSTM algorithm's accuracy values for various accuracy metrics, where LSTM with Adam observes highest accuracy and LSTM with SGD combination shows very low accuracy results when compared to other optimizers with LSTM. The accuracy values for the same is plotted in terms of graph and is depicted in Fig. 3.

TABLE III depicts Simple RNN algorithm's accuracy values for various accuracy metrics, where Simple RNN with Adam is been observed with highest accuracy when compared to other optimizers. The accuracy values for the same is plotted in terms of graph and is depicted in Fig. 4.

TABLE IV depicts GRU algorithm's accuracy values for various accuracy metrics, where GRU with Adam observes highest accuracy and GRU with SGD combination shows very low accuracy results when compared to other optimizers with GRU. The accuracy values for the same is plotted in terms of graph and is depicted in Fig. 5.

Based on the obtained accuracy results, TABLE V depicts low accuracy values observed for GRU and LSTM algorithm when experimented with SGD optimizer for multiple accuracy metrics.

With both LSTM and GRU algorithm optimizer SGD was common. As per the study, instead of using the entire dataset

TABLE II
PERFORMANCE METRICS OF LSTM RECURRENT LAYERS AND OPTIMIZERS

Recurrent Layers	Optimizer	Accuracy	Binary Accuracy	Categorical Accuracy	Mean Square Error	AUC	F1 Score	Precision
LSTM	Adam	0.9660	0.9986	0.9927	0.0055	1	0.9867	0.9927
LSTM	RMSprop	0.9830	0.9984	0.9684	0.0013	1	0.9402	0.9780
LSTM	SGD	0.0631	0.9744	0.0607	0.0248	0.6527	0.0066	0.0000e+00

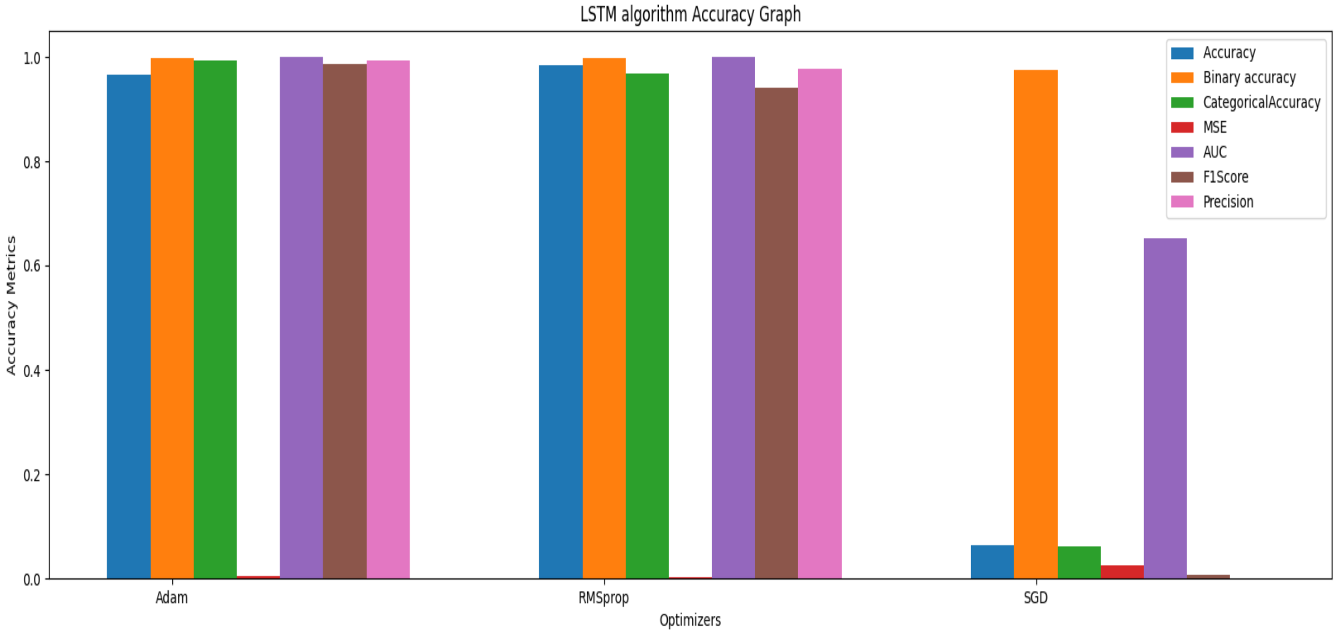

Fig. 3. Accuracy of LSTM Algorithm

TABLE III
COMPARISON OF OPTIMIZERS FOR SIMPLE RNN

Recurrent Layers	Optimizer	Accuracy	Binary Accuracy	Categorical Accuracy	Mean Square Error	AUC	F1 Score	Precision
Simple RNN	Adam	0.9951	0.9998	0.9951	1.53528e-04	1	0.9904	0.9927
Simple RNN	RMSprop	0.9830	0.9993	0.9903	2.2021e-04	1	0.9952	0.9903
Simple RNN	SGD	0.7961	0.9890	0.8824	0.0095	0.9951	0.7754	0.9902

for each iteration SGD, selects only a single random training example (or a small batch) to compute the gradient value and revise the model parameters. Randomness is outlined into the optimization process because of random selection, due to frequent updates noise increases, with every single sample. SGD is best suited for large datasets.

As per the observations, out of three optimizers used in this study Adam or RMSprop is preferred for better accuracy. Among the deep learning algorithms used in the proposed study accuracy for LSTM and GRU decreases with varying parameters. Simple RNN delivers good accuracy results with varying metrics. RNN is considered simpler and fast in training than LSTMs as they have fewer parameters and computations.

In order to improve the low accuracy results for the cases observed in Table V the epochs count was increased which permits the model to learn more complex patterns in the data. But only increasing the epochs will not increase the performance rate of the model there was a need to change batch size value. Along with count of epochs batch size was also modified.

It was observed with epochs count set to 200 and Batch size set to 1 there was drastic increase in accuracy metric which was very low otherwise, in particular better accuracy was observed when batch size is set between 1 to 3. With revised epoch and batch size value, increased accuracy results for optimizer SGD are tabulated in the TABLE VI for GRU algorithm and LSTM algorithm in TABLE VII. Graphically represented the same in Fig. 6. and Fig. 7 respectively.

Further for other accuracy metrics for algorithm LSTM and GRU with optimizer SGD, whose accuracy was observed very low, improved on setting epoch count 200 and batch

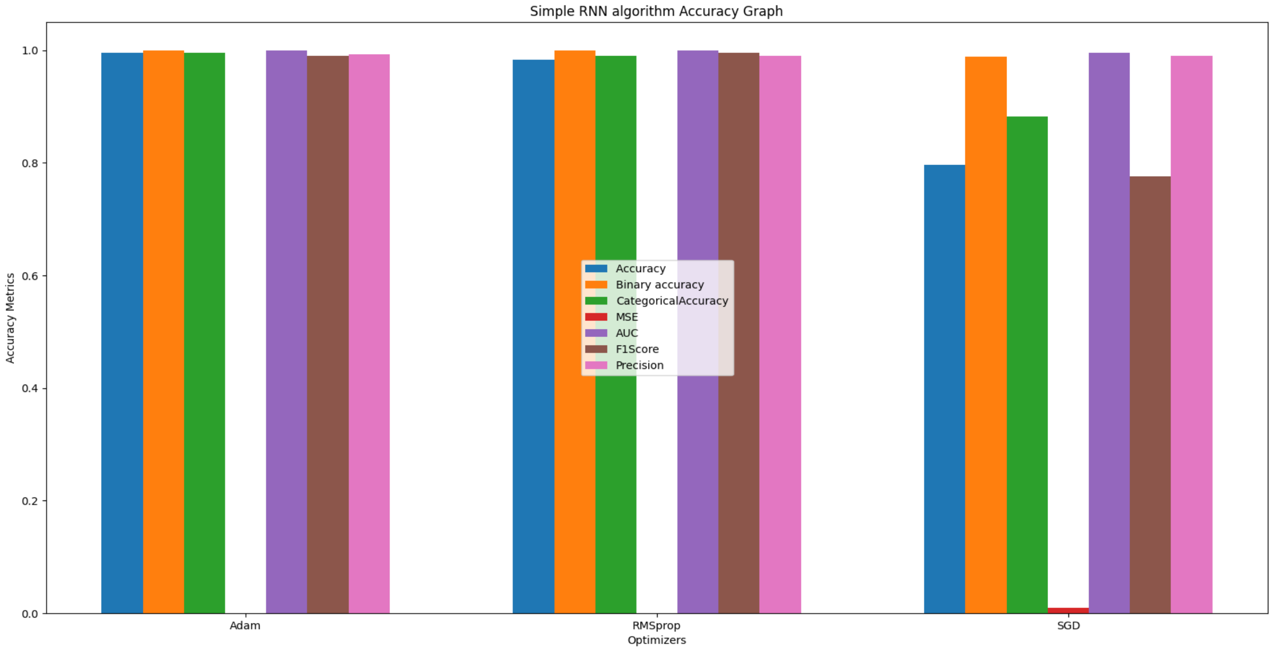

Fig. 4. Accuracy of Simple RNN Algorithm

TABLE IV
PERFORMANCE METRICS FOR GRU MODELS WITH DIFFERENT OPTIMIZERS.

Recurrent Layers	Optimizer	Accuracy	Binary Accuracy	Categorical Accuracy	Accuracy Metric		F1 Score	Precision
					Mean Square Error	AUC		
GRU	Adam	0.9903	0.9993	0.9879	4.2995e-04	1.0000	0.9791	0.9927
GRU	RMSprop	0.9223	0.9973	0.8981	0.0066	0.9989	0.8810	0.9616
GRU	SGD	0.0631	0.9744	0.0655	0.0248	0.6530	0.0067	0.0000e+00

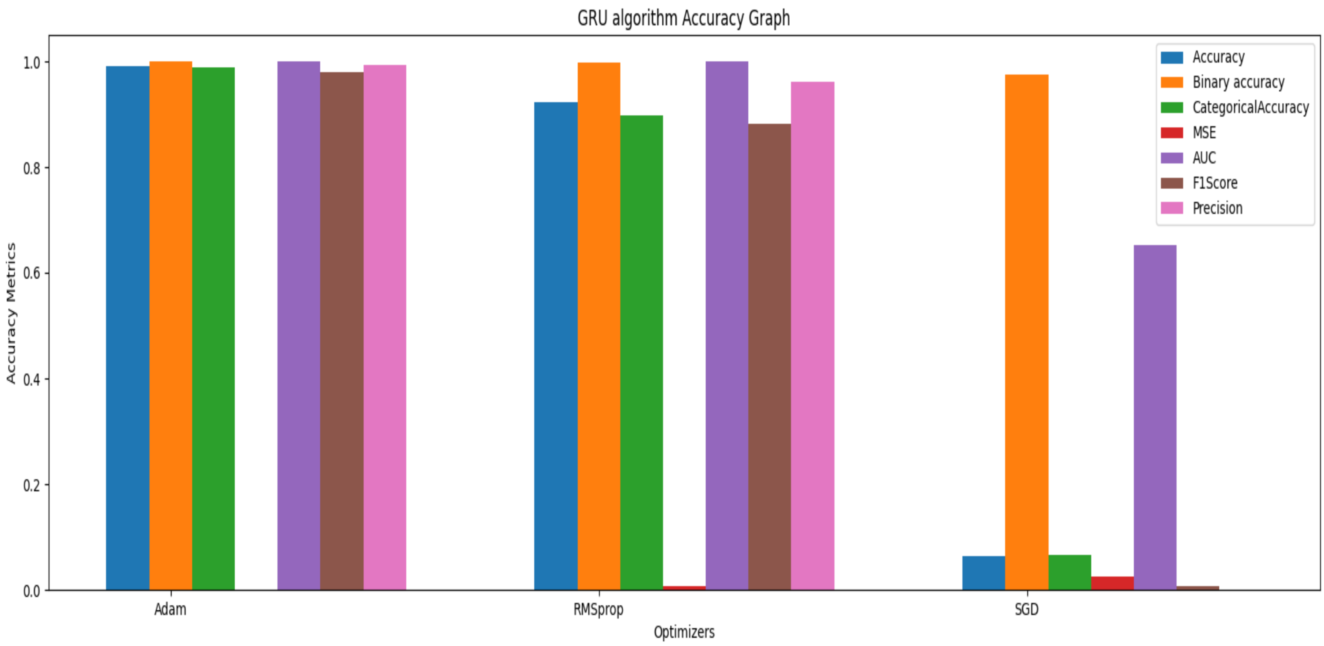

Fig. 5. Accuracy of GRU Algorithm

TABLE V
PERFORMANCE METRICS OBSERVED FOR MODELS WITH LOW ACCURACY.

Recurrent Layers	Optimizer	Accuracy	Binary Accuracy	Categorical Accuracy	Accuracy Metric		F1 Score	Precision
					Mean Square Error	AUC		
LSTM	SGD	0.0631	0.9744	0.0607	0.0248	0.6527	0.0066	0.0000e+00
GRU	SGD	0.0631	0.9744	0.0655	0.0248	0.6530	0.0067	0.0000e+00

TABLE VI
GRU WITH SGD INCREASE IN ACCURACY

RecurrentLayer	EpochCount	Optimizer	BatchSize	Accuracy
GRU	50	SGD	1	0.20
	200		4	0.3932
	200		3	0.716
	200		2	0.9587
	200		1	0.9927

TABLE VII
LSTM WITH SGD INCREASE IN ACCURACY

Recurrent Layer	Epoch Count	Optimizer	Batch Size	Accuracy
LSTM	50	SGD	1	0.3617
	200		4	0.7354
	200		3	0.9709
	200		2	0.9939
	200		1	0.9951

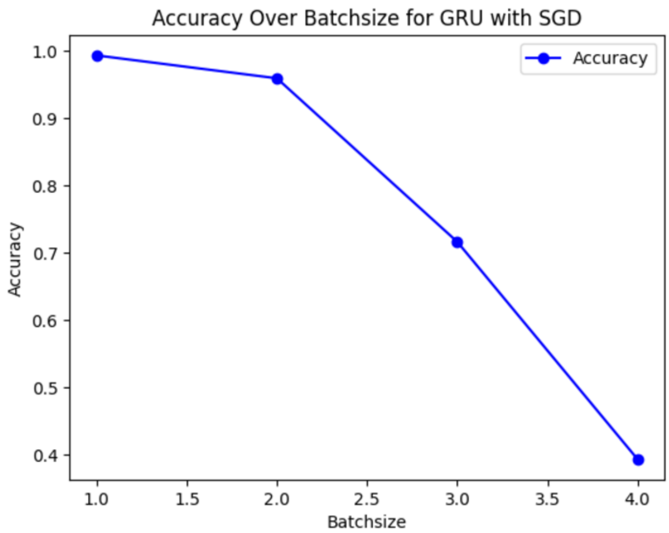

Fig. 6. Increase in Accuracy of GRU with SGD

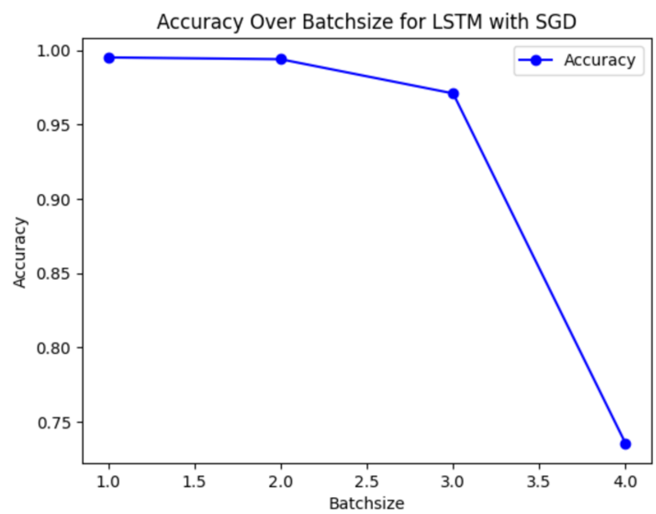

Fig. 7. Increase in Accuracy of LSTM with SGD

size 1. Increased accuracy values for metrics categorical accuracy, F1 score and Precision are tabulated in the TABLE VIII below.Complete comparision of the same is provided in TABLE X.Comparison of the performance metrics with low values when epoch count was set to 50 and batch size =16 with epoch count=200 and batch size=1 is shown graphically in Fig. 8. and Fig. 9 respectively.When Neural network algorithms Simple RNN,LSTM and GRU is compared with other algorithms like Naive Bayes,Logistic Regression and BERT models.The Accuracy and F1 Score values of Simple RNN is comparatively better than other algorithms proving neural network algorithms gives better results .The accuracy and F1 Score values is taken into consideration so that it could be compared with other models.The values are tabulated in TABLE IX. Graphically it is depicted in Fig. 10.

VII. FUTURE SCOPE

Trustworthiness of any chatbot is measured by the accuracy in response to queries [4]. Accuracy could be measured in terms of the different algorithms used in the working of the chatbot and also measured in terms of user feedback on how ethically sound the chatbot application is. Efficiency of an algorithm used in chatbot could be quantified or could be measured, but weighing efficiency of a chatbot based on ethical principles [16] is most of the times a theoretical concept and cannot be measured. In this paper efficiency measure of chatbot results relies on algorithms and various other technical factors. But there are many other ethical factors [29] like fairness [31], transparency [28], explainability [30][36] and many more, that could contribute towards trustworthiness of a chatbot. Further the trustworthiness of the chatbot could be considered for measuring the accuracy of a chatbot. Which could realistically build trust of end users over choice of selecting which chatbot application to use for

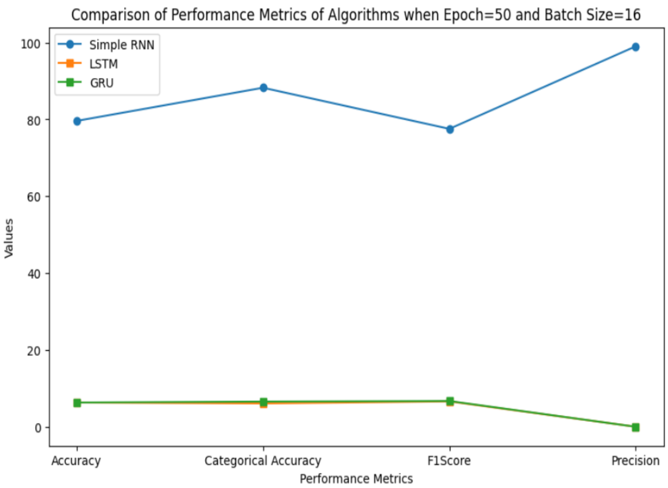

Fig. 8. Comparison of Performance metrics with optimizer SGD when Epoch=50 and batch size=16

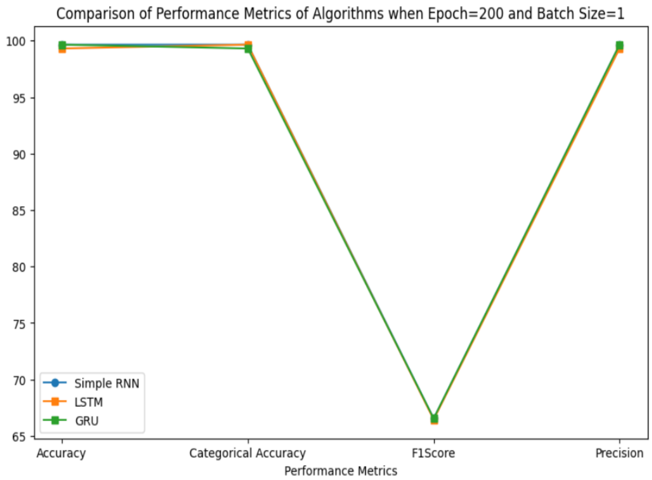

Fig. 9. Comparison of Performance metrics with optimizer SGD when Epoch=200 and batch size=1

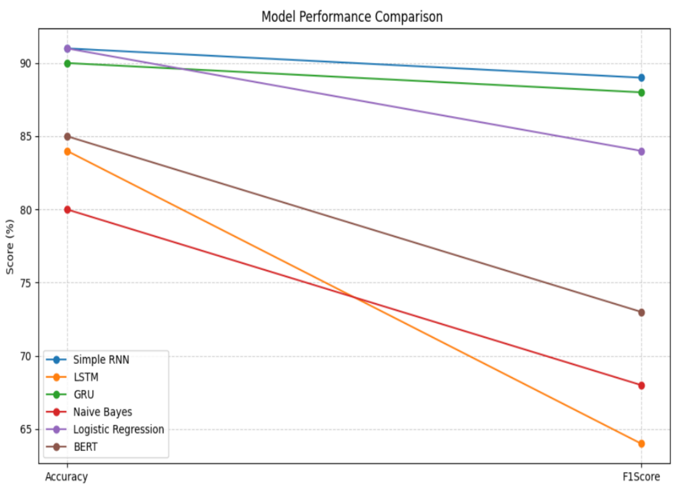

Fig. 10. Comparison of Model Performance

their day-to-day tasks.

VIII. Conclusion

Today we are in a world where almost every application we use is AI based, the forthcoming generation will be completely AI based, where we cannot avoid using AI. In the near future AI will not be an option it will be a compulsion, that's when trust plays a prominent role. When we say trust with respect to AI applications, it could be relying on how and which techniques application makes use of to give the accurate results. If techniques used are right, the results obtained are also right and trustworthy. So, to measure the trustworthiness of any Application we need to check accuracy obtained on using an algorithm with respect to that application. Accuracy becomes a deciding factor for predicting trustworthiness of an application. The choice of algorithm is conditionally dependent on type of application and requirement of the user. In our experiment out of the three neural networks chosen simple RNN proves to give better accuracy with all the three optimizers Adam, RMsprop and GRU, than LSTM and GRU algorithm.

TABLE VIII
Performance metrics observed for models with low accuracy.

Recurrent Layers	Optimizer	Accuracy Metric		
		Categorical Accuracy	F1Score	Precision
LSTM	SGD	0.9150	0.9271	0.9786
GRU	SGD	0.5704	0.3783	0.7815

TABLE IX
Comparison of Accuracy and F1 score of algorithms

Algorithm Type	**Algorithm Name**	**Accuracy**	**F1 Score**
Neural Network	Simple RNN	0.91	0.89
Neural Network	LSTM	0.84	0.64
Neural Network	GRU	0.90	0.88
Classification Algorithm	Naive Bayes	0.80	0.68
Classification Algorithm	Logistic Regression	0.91	0.84
Language Model	BERT	0.85	0.73

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TABLE X
COMPARISON OF OPTIMIZER SGD FOR SIMPLE RNN,LSTM AND GRU ALGORITHMS

Recurrent Layers	Optimizer	Accuracy	Binary Accuracy	Categorical Accuracy	Mean Square Error	AUC	F1 Score	Precision
Simple RNN	SGD	0.9965	0.9615	0.9965	1.3288e-04	1	0.6655	0.9927
LSTM	SGD	0.9931	0.9996	0.9965	1.2954e-04	1	0.6644	0.9931
GRU	SGD	0.9965	0.9996	0.9931	1.5103e-04	1	0.6655	0.9965

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