INTELLIGENT CONVERSATIONAL MODEL FOR MENTAL HEALTH WELLNESS

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Abstract: Mental Health affects how we think, feel and act. Mental Health Problems (MHP) affect our thinking, behavior and mood. The Conversational Model which is being proposed for MHP is an AI based model for slight to moderate measurement users who have MHP like depression, mental stress. The learning techniques used in this work is a neural framework exhibit for setting up the model to give activities and solutions for the users. Here, we are using NLTK for Python to analyse text. The human responses are captured by designing an intelligent engine. The dataset used to train this neural framework is designed and curated under the supervision of psychologists. Here the model helps people with light to moderate level of MHPs by giving simple and easy to perform activities and solutions for their appropriate problems. The model identifies particular phrases which is matched with the data corpus and helps providing appropriate solutions for that particular problem. The Data Corpus has been developed under the guidance of Psychiatrists to help users with MHPs. The user must pass a preliminary test before getting access to the Chat bot.

Keywords: Mental Health Problem, Neural Networks, Conversational Model, Artificial Intelligence/Deep Learning, Natural Language Processing.

1. Introduction

Mental health is extremely vital in the lives of humans. Our emotional, psychological, and social well-being are all included. It has an impact on how we think, feel, act, and act. It enables us to assess our stress tolerance and make decisions. Mental health is crucial at all stages of life, from childhood to adolescence and maturity. If a person has Mental Health Problems throughout their lives, their thinking, emotions, and behaviour may be altered. This could result in mental health problems, depression, or even suicidal ideation. This has become a severe problem, and there hasn't been enough attention paid to this particular health issue. The only way to solve this is to consult a psychologist or a doctor. There are several factors which comes into play while determining MHI such as Biological factors, such as genes or brain chemistry, Life experiences, such as trauma or abuse, Family history of mental health problems. The large population in India causes a lot of problems and as it says in the survey done by the WHO, MHPs will lead to a huge economic breakdown and might setback the country's development rate 10 years back especially after the COVID-19 pandemic. According to a research paper [1], the cases of COVID-19 will not be decrease in the foreseeable future in fact it will grow exponentially. Because of this growth, multiple lockdowns have been implemented and people are constantly staying in home and majority of the youngsters are suffering from MHIs. The Mental Health of each and every citizen of the country is important as it contributes towards the development and economic stability of the country [2].

2. Significance of the study

The System can simulate a conversation with a user in Natural Language. It is often described as one of the most advanced and promising expression of interaction between Humans and Machines. From technical point of view, it can also be called as a Chat Bot. There are 2 different tasks at core of this Conversational System: User Request Analysis and Returning the Response.

3. Review of related studies

Yu et, al. (2016) conducted an experiment on Retrieval Based Conversational AI Conversational Model with the Ubuntu corpus. The experiments are done using different Neural Network Models such as LSTM, CNN, BiLSTM and have used Sequential Matching Network as their final model. They have got the highest accuracy of 92% with the Sequential Matching Network[3]. **Setiaji and Wibowo (2016)** created a model using Relational Database Management System (RDBMS) in MySQL and Java for training the model. For the Conversational System NLP was done in Indonesian Language which divides the sentence into words and makes a pattern-matching operation. They have made use of variety of functions to cover all aspects of NLP such as similar words or phrases, spelling correction, tokenisation etc. [4] **Surendran, et .al. (2020)** developed Retrieval based AI Learning system, which matches and retrieves data from corpus which is similar to the user's request. Here they have stored the data in JSON format and have used NLP techniques to make the model efficient. Python is the programming language used to develop this bot. They have used a simple Multilayer Perceptron as their DL model. They have experimented with different Activation and Optimization functions. Their model was able to achieve a 95% accuracy.[5] **Singh et. al. (2018)** created a framework to create a Conversational System that may be used by independent businesses to replace customer service. The AI is at the heart of the proposed framework. To develop a reaction model, the suggested framework uses Tensor Flow to create a neural system and train it with a plan document. User Interface, Neural System Model and NLP Unit, and Feedback System are the three sections of the framework. Based on previous experience, it determines how to react. Regardless, they used certain NLP capabilities, but the actual process through which the reaction is generated is based on AI. The exactness of the Conversational System is genuinely proportional to the size of the plan record used to create it. It is reasonably straightforward to construct the objective records that will yield a certain dimension of precision with a small amount of space. This method is obvious in a situation where space is restricted and the client has a high level of importance. [6] **Rahman et al. (2017)** looked on issues with Conversational Systems that were related to NLP and AI. The moves identified with NLP include distinguishing sentences of similar relevance from a variety of different types of sentences. The inventor has also looked into and divided the current stage into three categories, namely No programming systems, Conversation-Oriented systems, and Platforms by IT behemoths' systems. They discussed the phases for non-software engineers in the main class, which do not require any programming knowledge, such as Chatfuel, ManyChat, and Motion.ai. In the second class, ALML is used as a language to display client interaction in the UI. They discussed the stage established by tech behemoths such as Google's api.ia, IBM's Watson, and Amazon's Lex in the last. [7] **Sameera and John (2015)** performed a survey, and the results were used to compile a list of selected research articles over the last decade that focused specifically on Conversational Systems planning systems. The NLTK Python package was investigated in this paper for converting over the sound voice into important sentences. The system is divided into three sections: responder, classifier, and graphmaster, with responder serving as the interface between bot and client. The classifier is the central layer, which routes, splits, and standardises the data before AIML completes it. The last layer, chart ace, is used for things like coordinating. [8]

The major limitations of the above work are, usage of generic data corpus and have used NN models which are less dense, it is mainly concentrated on Indonesian Language and have not used any type of NN models with data corpus used is very small and generic. The NN models used are not dense they had only two layers of neurons. The Proposed Conversational Model is focused on overcoming the above said limitations by increasing the density and layers of the Neural Network with a larger data corpus specifically targeting audience with MHPs.

4. Objectives of the study

The objective of this endeavour is to attempt temporary solution for MHPs and MHIs for the individuals. The model involves two phases that are Problem Expression stage and the Solution for the said Problem stage. The model uses significant learning development to set itself up with the diverse Solutions to each MHP and Injury cases. The main focus of this model is to achieve most apt solution for the given problem of MHP or Basic Injury using Deep Learning to achieve highly accurate solutions.

5. Hypotheses of the study

- Awareness on Mental Health is moderate among normal citizens.
- There has been an increase in MHPs since the pandemic and it shows no significant decline since then.
- People are still unaware of the effects of MHPs in their daily life and how it affects their behavior.
- People are not ready to come out to light and accept they have MHPs like Depression etc due to Social Barriers and pre-notions.

6. Dataset and methods

The Neural Network of the Conversational Model is dense and multilayer for accurate classification of the data corpus and precise conversation. The Data Corpus is the heart of this Model and plays a very important role. The data corpus undergoes different NLP techniques for easier machine understanding. The Neural Network is a Multilayer Deep Feed Forward Neural Network which has dense neurons and multiple layer which is trained and experimented in different methods.

6.1. Dataset

The dataset or data corpus is the heart of this project. The data corpus is created under the direct supervision and guidance of Psychiatrists. The doctors have provided materials from different resources such as **Kilburn and**

Whitlock (2009) [9]. Also they provided solutions to different types of MHPs for people who have light to moderate MHIs. The different types of MHPs/MHIs covered in this work are Depression, Sadness, Laziness, Loneliness, Frustration and many more. Figure.1., Figure.2. and Figure.3. are some samples of the Data Corpus.

Figure.1 Data Corpus Sample 1


```
{
  "tag": "greeting",
  "patterns": ["Hi", "Hey", "How are you", "Is anyone there?",
"Hello", "Good day"],
  "responses": ["Hey :-)", "Hello, How are you doing today?",
"Hi there, How are you feeling today?", "Hi there, how is it
going?"],
  "context": [""]
}
```


Figure.2 Data Corpus Sample 2


```
{"tag": "animal bite",
    "patterns": ["How do you treat a animal bite?", "How do
you treat a monkey bite?","How do you treat a dog bite?",
"what to do if i get a animal bite?", "Which medicine to take
if I get a monekey bite?", "How to cure dog bite?", "i got bit
by a dog"],
    "responses": ["1)Wash the wound with soap and warm water.
2)Gently press a clean cloth over the wound to stop the flow
of blood. 3)Apply an antibacterial ointment to the wound.
4)Cover with a sterile bandage. 5)Watch for signs of
infection. 6)Seek help if you suspect infection or possible
exposure to rabies, or if the wound is severe."],
    "context_set": ""
  }
```


Figure.3 Data Corpus Sample 3


```
{
  "tag": "lonely",
  "patterns": ["I feel lonely", "I am all alone", "I feel
alone", "I am alone", "I think I am lonely", "I think I am
alone", " I have been alone all my life", "I have been lonely
all my life"],
  "responses": ["I understand how you feel. It can take a huge
toll on your mental health. \nTry theses methods to get rid of
your loneliness. \n1. Connect to people through sports,
hobbies, passions or interests. \n2. Borrow or adopt a dog and
go walking. \n3. Talk to senior citizens. \n4. Start a journal
to track your thoughts and feelings. \n5. Practice meditation.
"],
  "context": [""]
}
```


The data corpus also has First Aid solutions for basic injuries. These solutions are recommended by Nurses and Doctors when there is an emergency. The data corpus covered a wide variety of injuries such as Cuts, Stings, Splinters, Cough, Vertigo etc

The data corpus is stored in a JSON format and file. The data corpus is used to train the Conversational System. The data contains different “INTENTS” and for each intent there is a “TAG” which is a class label for the classification process done by the Deep NN. For each tag there are different "PATTERNS" and "RESPONSE" for the tag contained in a list.

6.2. Proposed System

People having mild to moderate MHPs can be treated easily with basic activities and solutions. The strategy is to identify the user's level of MHP and treating them accordingly. This strategy can also be used for basic First Aid. The Proposed System will concentrate mainly on users with mild to moderate MHPs and light to medium injuries related to basic First Aid. Here the system will use a specialized dataset created under the guidance and supervision of two Psychiatrists, who have provided basic and easy solutions that the user can do. The First Aid solutions are also basic and simple with regards to the injuries.

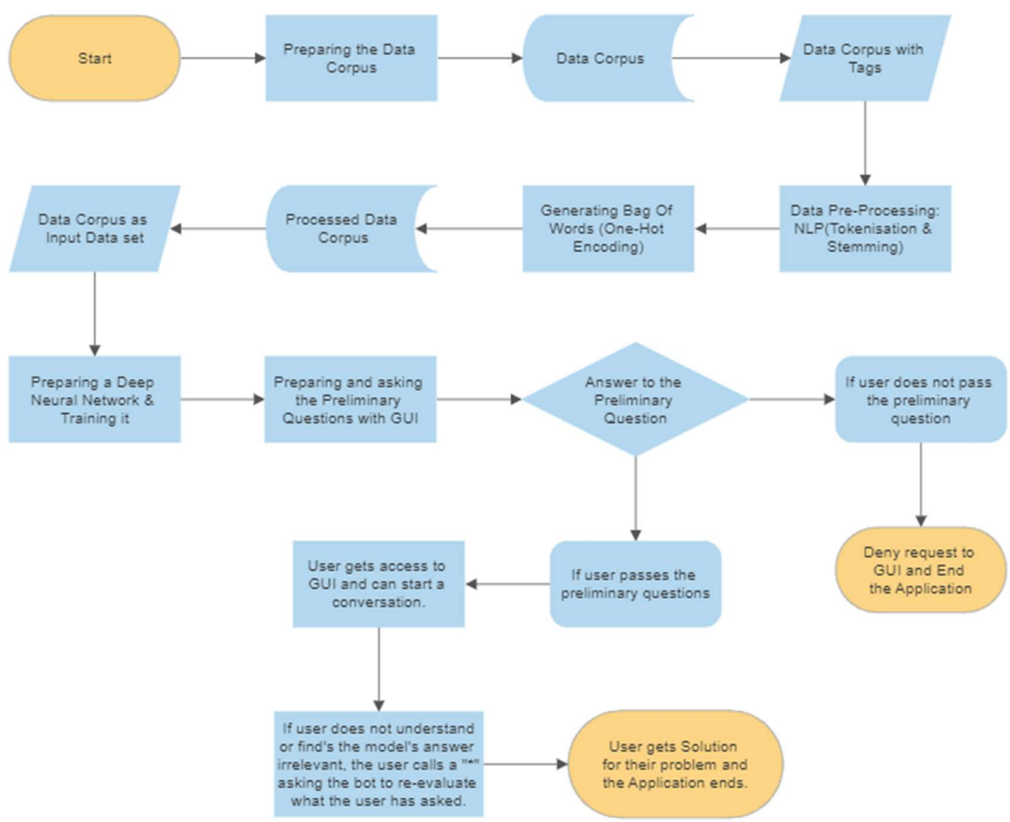
The Proposed Model will be using and experimenting with 2 types of Deep Feedforward Neural Network with different Activation and Optimization functions. The best performing model with highest accuracy and least loss will be selected as the final model. The user will be presented with a Chat Window where they can type their queries and get solutions accordingly. The user will get access to the Chat Window when they clear their Preliminary Assessment to judge the level of MHP they are having. They can also access the Chat Window if they have any First Aid emergencies.

The Proposed Model is developed using different Software's and Tools such as Python, PyTorch, Google Collaboratory, PyCharm, Tkinter, NLTK Package, JSON File format, NumPy etc.

6.3. Methodology

The system is required to give specific answers or solutions for a few particular quires asked by the user. Hence a Retrieval Based System is being used in this situation instead of a Generative Based System.

Flowchart.1. Algorithm for the Conversational System

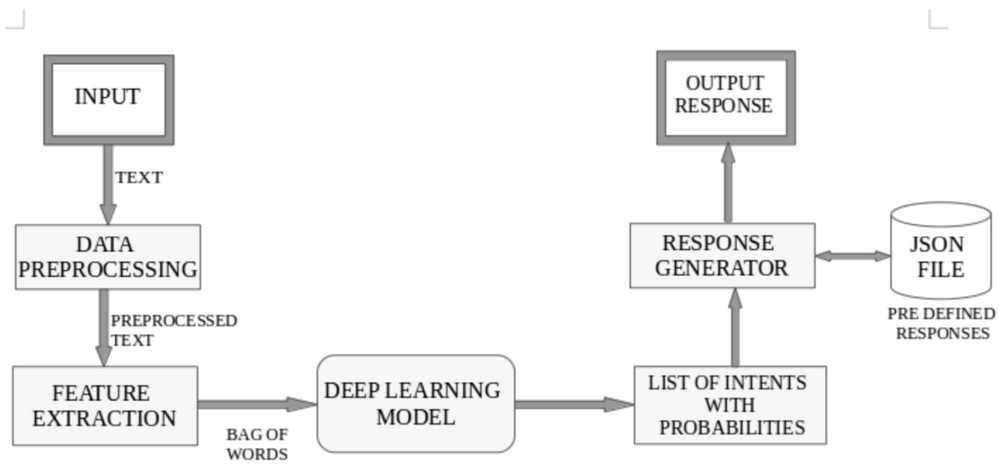


6.3.1. System Overview

While creating the system model, the primary goal of developing a Deep Learning [10] model, the input questions are being used to steer the conversation in a more meaningful direction. The Proposed System uses a manually created MHP Solution and First Aid querying dataset and generates relevant responses using a pre-defined repository.

PyTorch the Deep Learning Python Library is being used in the Proposed System. The System is experimented with two Deep Learning models from Torch named Sequential and Linear. Figure1.1 depicts the basic architecture of the proposed Retrieval Based system. As demonstrated, the overall system architecture can be divided into several sub modules. Data is regarded as the most important component of Conversational system. If the system must be, truly conversational, the dataset is an important factor to consider. It's difficult to create a conversational system with moderate intelligence because it necessitates a lot of interaction data and interdisciplinary methodologies.

Figure.4. System Overview



In order to improve accuracy, a data set is manually created. The system typically operates in a closed domain because it is retrieval-based. As previously stated, a closed domain of MHPs and First Aid data is taken into account. The first task completed as part of the system implementation was data set preparation. Data can also be collected from the internet, but the difficulty is that much of the data isn't in the format that is required. In this case, it is preferable to develop our own data corpus. It may appear to be a tedious chore at first, but it will ultimately aid in the generation of meaningful solutions.

The data set should be updated at a given period of time, and the model should be retrained to increase accuracy. Otherwise, the information will become obsolete. It's recommended to manually add the results of those queries to the data set when a user repeatedly asks a question that isn't documented in the repository. This strategy will dramatically boost the system's efficiency, resulting in fewer unanswered enquiries. The dataset is a collection of JavaScript objects that specifies various tags that correspond to various word patterns and is saved as a Json file that contains the intents.

Following the creation of the dataset, various pre-processing processes are used to clean the information. The pre-processing task is critical when dealing with any NLP task. The information has been pre-processed to remove any content that does not provide useful information.

The duty of pre-processing is carried out here over the entire dataset, which includes various user input enquiries and responses, as well as when a specific input, such as Patterns, is provided by the user. The text pre-processing phase employs a variety of tools and libraries. The Natural Language Tool Kit (NLTK) Library and several string handling routines in Python were used to complete the subtasks in the text pre-processing phase.

After the Feature Extraction, the desired DNN Model is created and is trained with the training data set which was created in the previous module. The data of the trained models are stored in a separate file which is later used to deploy the DNN model for the Conversational System.

A Graphic User Interface (GUI) is developed for the Conversational system, so that the user the user can converse with the system easily without any sophistication.

6.3.2. Retrieval Based Model

The Proposed System is a Retrieval-Based system that focuses on one area in particular. For implementation, a closed domain of Solutions for MHPs and Basic First Aid solutions is used. The notion of directed flows or graphs is used by retrieval-based bots. Essentially, these bots are programmed to rate the best response from a limited number of options.

The developer enters the responses manually or uses a knowledge base of previously collected data. The system is programmed in such a way that there will be a collection of questions that the user will typically ask several times in multiple ways, as well as a set of responses to those questions. It enables the creators to take control of the experience and tailor it to the needs of its users. It's great for user service, lead generation, and feedback bots with specific goals. The model can be tailored to the needs of specific user needs, here in this case to the needs of users with MHPs and First Aid issues.

Figure.5. Retrieval Based Model

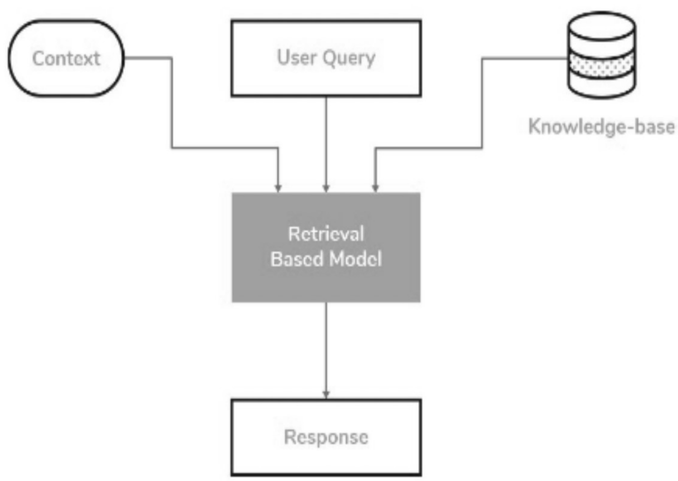


Figure.5. depicts the fundamental architecture of the retrieval-based system. The system simply searches the knowledge library for acceptable replies using any of the matched metrics given a user input utterance as the query. The problem of query speech and potential replies is regarded as the heart of retrieval-based conversational systems.

By determining the query's main intent, the model will determine the query's context. A comparison is made between the user's query and the set of queries previously saved in the repository. The inner-product of two representative feature vectors for the queries and candidate responses is a common method for matching. When it comes to matching, a variety of strategies are frequently used for Conversations in a Retrieval-Based system.

For retrieval utilising Deep Neural Networks, a set of matching metrics has been suggested. Sentences are often compared by word-by-word matchings in a pairwise matching method known as sentence pair modelling. Chain based matching has also been demonstrated to be beneficial by integrating sentence information as a chain sequence. In chain-based matching, the modelling of the second sentence is not blind to the modelling of the first phrase. Although not all of these methods were created with conversation in mind, they are useful for short-text matching tasks and serve as a solid foundation for Retrieval-Based conversational investigations.

6.3.3 NLP Techniques

When dealing with any NLP task, the pre-processing task is considered essential. The data corpus we're looking at has been pre-processed to exclude any content that isn't useful. Pre-processing is done here in the full dataset, which encompasses various user input inquiries and responses, as well as when the user provides a specific input. Table.1. list the various tools and libraries utilised during this period. [11]

Table.1. NLP Pipeline Packages

Task	Method Used
Tokenization	NLTK
Stemming	NLTK
Case Conversion of Words	Python String Handling Functions
Creating the Bag of Words	NumPy

The text pre-processing uses NLP techniques such as

- **Tokenization**: A string is broken down into meaningful components, such as words.
- **Stemming**: Generate the terms' root forms. It's a rudimentary heuristic for chopping off the ends of words.
- **Case conversion of words**: All words are converted to lowercase.
- **Bag of Words (BoW)**: All the converted words are stored in an array i.e. One Hot Encoding.

6.3.4 Deep Multilayer Feed Forward Neural Network

Any simple classification task can be performed using a Deep Multilayer Feed Forward Neural Network (DMFFNN) with at least two intermediate layers in addition to the input and output layers. For complex pattern mapping and classification tasks, such an DMFFNN can be used.[12] Since the Proposed Conversational Model is not Generative based model, the DMFFNN will suffice for the required task.

The Conversational Model is built using 2 types of DMFFNN, Linear and Sequential FFNN. Each of these network consists 7 layers with dense number of neurons. The first layer has 1024 neurons, the density of each layer is reduced by half ie the second layer has 512 neurons subsequently the last layer has 32 neurons.

7. Experimentation, Results and Discussions

7.1 Experimentation

Here the two different Deep Feedforward Neural Network, Linear and Sequential models are experimented with different Activation and Optimizers. All the experimentation is done using Google Collaboratory.

7.1.1 Activation Functions

Two Non-Linear of Activation functions, Rectified Linear Unit (ReLU) and Sigmoid are being used here to experiment with the proposed model since they are easier for the model to adapt to a range of data and differentiate between the outcomes.

Rectified Linear Unit is an easy to compute activation function. It is mathematically represented by this function

$$f(x) = max(0, x)$$
$$f'(x) = \partial f(x) / \partial x = 0 \text{ if } x < 0 | 1 \text{ if } x > 0$$

ReLU outputs the input value itself if it is positive, else it outputs zero, i.e. **f(1) = 1, f(-1) = 0**

Sigmoid is an easy to compute activation function. It is mathematically represented by this function

$$f(x) = 1/1 + e^{-x}$$
$$f'(x) = \partial f(x)/ \partial x = f(x) * (1- f(x))$$

It is a monotonic function, but its derivative is not. The major advantage of this function is it lies between the **range (0 to 1).**

7.1.2. Optimizers

Three types of Optimization functions Adam, ADAGrad and RMSProp are used to get better results with least loss.[13][14][15][16]

AdaGrad or Adaptive Gradient algorithm satisfies the decay of learning rate for parameters. It is mathematically represented by this function

$$\Omega_{t+1} = \Omega_t - \eta/\sqrt{(\upsilon_t)} + \varepsilon \nabla\Omega_t$$

The denominator term $\sqrt{(\upsilon t)}$ serves to regulate the learning rate η, For dense features, υt is larger, $\sqrt{(\upsilon t)}$ becomes larger thereby lowering η, For sparse features, υt is smaller, $\sqrt{(\upsilon t)}$ becomes smaller and lowers η to a smaller extent. The ε term is added to the denominator $\sqrt{(\upsilon t)} + \varepsilon$ to **prevent** a **divide-by-zero error** from occurring in the case of very sparse features i.e. where all the data points yield zero up till the measured instance.

To overcome the aggressive decay of AdaGrad, **RMSProp** algorithm is considered as it decays the denominator and prevents from rapid growth. It is represented by this function

$$\upsilon_t = \beta * \upsilon_{t-1} + (1 - \beta)(\nabla\omega_t)^2$$

Adam is a combination of both RMSProp and AdaGrad. This combination ensures a smooth Training and also prevents erratic updates in the beginning of training. It is represented by these functions which are quite similar to AdaGrad and RMSProp.

$$m_t = \beta 1 * \upsilon t{-}1 + (1 - \beta 1)(\nabla\Omega_t)$$

$$\upsilon_t = \beta_2 * \upsilon_{t-1} + (1 - \beta_2)(\nabla\Omega_t)^2$$

$$\Omega_{t+1} = \Omega_t - \eta/\sqrt{(\upsilon_t)} + \varepsilon\, m_t$$

Here, the first history m_t is used to make the update, ensuring that the history of derivatives is used to calculate the current update. The second derivative v_t is used to regulate the learning rate based on density or sparsity of the feature.

7.2. Experimentation Process

As explained above the 2 types of DMFFNN, Linear and Sequential are experimented with a combinations of sets of Activation Functions and Optimizers. There are totally 9 combinations of 2 NN Models, each with 2 different Activation Function and with 3 Optimizer as seen in Table.2.

Table.2. Models, Activation & Optimizers

NN Models	Activation Functions	Optimizer
Linear DFFNN	ReLU	Adam
		AdaGrad
		RMSProp
	Sigmoid	Adam
		AdaGrad
		RMSProp
Sequential DFFNN	ReLU	Adam
		AdaGrad
		RMSProp
	Sigmoid	Adam
		AdaGrad
		RMSProp

7.3. Comparison of Performance and Training time of the Models

Each of these models are trained with a fixed Hyper Parameters where the number of Epochs are 1000, Batch Size of 8 and the Learning Rate is set to 0.001. The Table.3. shows the Loss of each model with that particular Activation Function and Optimizer. The Table.4. shows the Training time taken by each models.

Table.3. Comparison of Loss of the Models

OPTIMIZERS	ACTIVATION FUNCTIONS			
	Linear DFFNN with ReLU	**Linear DFFNN with Sigmoid**	**Sequential DFFNN with ReLU**	**Sequential DFFNN with Sigmoid**
ADAM	0.0000	1.1691	0.0000	0.7258
ADAGrad	0.1259	4.3733	0.0081	4.2715
RMSProp	0.0971	4.3863	0.0966	4.2952

Table.4. Comparison of Training time of Models

OPTIMIZERS	ACTIVATION FUNCTIONS			
	Linear DFFNN with ReLU	**Linear DFFNN with Sigmoid**	**Sequential DFFNN with ReLU**	**Sequential DFFNN with Sigmoid**
ADAM	26m 0s	12m 29s	28m 39s	10m 40s
ADAGrad	12m 16s	10m 10s	13m 6s	9m 27s
RMSProp	35m 45s	17m 29s	31m 17s	11m 17s

7.4. Results

From Table.3. and Table.4. each model regardless of the Activation Function under Adam Optimizer has had the least loss with respect to different Optimizer under same Activation. Both Linear and Sequential model with ReLU Activation and Adam Optimizer has the least loss ie 0.

7.5. Discussions

Both the DFFNN models, Linear and Sequential Models with ReLU and Adam has performed very well with 0.0000 loss. This is because Adam is a combination of two other Optimizers as explained in 3.1.2. Since it has the advantages of both the Optimizer it tends to outperform the other models.

8. Conclusion

In conclusion the Linear and Sequential DMFFNN Models with ReLU and Adam has the best performance and is used in the Conversational Model. The performance of these models is better when compared to other models with different Activation and Optimizers because:

Adam Optimizer is considered as the best among adaptive Optimizers and also it ensures a smooth Training of models and prevents erratic updates. Another major advantage of Adam is it works good with sparse data and also there is no need to focus on the Learning Rate manually.

Sigmoid Activation did not perform well as it transforms its input value into output value between the range (0 to 1). This led to the saturation of the Neural Network around 0 & 1. This causes the Neural Network to get struck at the Training Time leading to the Vanishing Gradient problem.

ReLU on the other hand takes an input value and directly outputs the input value if positive, else if it is negative it outputs 0. It combines the benefit of both Linear and Non-Linear Activation while allowing for complex relations to be modeled.

Hence these **Adam Optimizer and ReLU** Activation performed well when compared to the other models.

8.1. Acknowledgement

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