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FOREWORD

I warmly welcome all and sundry to the volume 3 issue 1 of Federal Polytechnic – Journal of Pure and Applied Sciences (FEPI-JOPAS) which is a peer reviewed multi-disciplinary accredited Journal of international repute. FEPI-JOPAS publishes full length research work, short communications, critical reviews and other review articles. In this issue, readers will find a diverse group of manuscripts of top-rated relevance in pure and applied science, engineering and built environment. Many of the features that you will see in the Journal are result of highly valuable articles from the authors as well as the collective excellent work of our managing editor, publishing editors, our valuable reviewers and editorial board members.

In this particular issue, you will find that Joseph and Adebanji provided innovative technology on light traffic control system. Ogunkoya and Sholotan engaged standard method for microbiological assessment of shawarma from Igbesa metropolis for possible microbial contamination. Ilelaboye and Kumoye unveiled the effect of inclusion of different nitrogen source on growth performance of mushroom. Ogunyinka et al utilized Fletcher Reeves conjugate gradient method as a robust prediction model for candidates' admission to higher institutions. Omotola and Fatunmbi examined the impact of thermal radiation with convective heating on magnetohydrodynamic (MHD), incompressible and viscous motion of non-Newtonian Casson fluid. Aako and Are meticulously investigated factors affecting mode of delivery using binary dummy dependent models. Abiaziem and Ojelade successfully synthesized biologically active silver nanoparticles using *Terminalia catappa* bark as the eco-friendly source.

In addition, Olowosebioba et al. assessed the rectifying effects of various diodes in power supply units using multisim circuit design software programme. Olujimi et al. successfully accomplished the use of fingerprint based biometric attendance system for eliminating examination malpractices with enhanced notification. Alaba reported the nutritional status assessment of school age children (6-12 years) in private primary school in Ilaro. Muhammed-lawal et. al. assessed the execution and effect of corporate social responsibilities and return to marketing. Awolola and Sanni's research was about achieving quality of engineering education and training in Nigeria using Federal Polytechnic, Ilaro as the case study. Oladejo and Ebisin expatiated on virtual laboratory as an alternative laboratory for science teaching and learning.

Finally, Aneke and Folalu investigated the prospect and problems of the hotels in Ilaro, Ogun State.

I would like to thank and extend my gratitude to my co-editors, editorial board members, reviewers, members of FEPI-JOPAS, especially the Managing Editor, as well as the contributing authors for creating this volume 3 issue 1. The authors are solely responsible for the information, date and authenticity of data provided in their articles submitted for publication in the Federal Polytechnic Ilaro – Journal of Pure and Applied Sciences (FEPI-JOPAS). I am looking forward to receiving your manuscripts for the subsequent publications.

You can visit our website (https://www.fepi-jopas.federalpolyilaro.edu.ng) for more information, or contact us via e-mail us at fepi.jopas@federalpolyilaro.edu.ng.

Thank you and best regards.

E-Signed
Prof. Olayinka O. AJANI

FEPI-JOPAS VOLUME 3 ISSUE 1 TABLE OF CONTENTS

https://fepi-jopas.federalpolyilaro.edu.ng Experimental

A Robust Prediction Model for Candidate's Admission using Fletcher-Reeves (FR) Conjugate Gradient Method

Ogunyinka, T. K., Dada I. D., Oni, O. O.& Ayemowa, M. O.
Department of Computer Science, Gateway (ICT) Polytechnic Saapade-Remo, Ogun State.
✉tkogunyinka@yahoo.com

Abstract

Selection of prospective candidates to a higher institution of learning based on candidate's choice of course of study is now becoming a herculean task, particularly when the carrying-capacity of two hundred and fifty–six higher institutions in Nigeria cannot admit over one million eligible candidates seeking admission yearly. Several works have been done in the past using Nave Bayes algorithm, Decision trees, K-Means algorithm, Random Forest and other Machine learning algorithms to predict Candidate's admission to higher institutions. Previous methods were confronted with pockets of shortcomings. These include required lengthy offline/batch data training, unable to learn incrementally or interactively in real-time, poor transfer of learning ability, and non-reusability or integration of modules etc. In this paper, a machine learning model was implemented using Fletcher-Reeves Conjugate Gradient algorithm to predict candidates' selection into a higher institution of their choice. The algorithm was implemented using python programming language. The algorithm was found to perform better than the Gradient Method with 89% prediction accuracy compared to 83% prediction accuracy of the gradient method.

Keywords:Candidate's Admission, Neural Networks, Optimization Algorithm, Prediction Model.

INTRODUCTION

The individual goal's achievement in life is a function of the educational level attainment. In order to realise this, every Secondary school leaving student in Nigeria strives very hard to pursue a higher education. However, securing admission into candidate's dream institution becomes a major concern to such candidates. With one hundred and seventy (170) Universities (NUC, 2020) and Eighty-six (86) Polytechnics (NBTE, 2020) spread across the nation, the choice of a higher Institution by a candidate seeking admission becomes more cumbersome as each institution sets some requirements for candidates to secure admission apart from the general requirements put up by regulating bodies such as West African Examinations Council (WAEC) and Joint Admissions and Matriculation Board (JAMB). Obviously, the carrying-capacity of only two hundred and fifty–six higher institutions in Nigeria cannot admit over one million eligible candidates seeking admission yearly. Several extant works have considered this problem using Nave Bayes algorithm, Decision trees, K-Means algorithm, Random Forest and other Machine learning algorithms to predict Candidate's admission to higher institutions (Sonawane, 2017). However, previous methods were confronted with pockets of shortcomings. These include required lengthy offline/batch data training, unable to learn incrementally or interactively in real-time, poor transfer of learning ability, and non-reusability or integration of modules etc.In this paper, we have implemented a machine learning algorithm using Fletcher-Reeves Conjugate Gradient Method (CGM) to predict the selection of a candidate seeking admission to Gateway (ICT) Polytechnic Saapade. In this work only candidates who have passed minimum of five 'O' level papers relevant to their proposed course of study are considered legible for selection.

Machine learning algorithms give computers the ability to learn from aggregated data which can be used for data manipulation, predict the output for new data and to classify data. Machine learning is used to address a specific problem. Almost all machine learning algorithms can be formulated as an optimization problem to find the optimal value of an objective function. Constructing an objective function is the first step in machine learning methods.The conjugate gradient method (CGM) is an optimization method that is applied in some specific areas in Computer Science, Mathematics, Physics, Economics (Dai, 2010). CGM can be used to solve linear equations and nonlinear optimization problem (Dai, 2010).

The general unconstrained optimization problem is given as

$$min\{f(x)|x \in R^n\} \quad (1)$$

Where $f: R^n \rightarrow R$ is continuously differentiable, $f(x)$is an objective function and $x \in R^n$is a vector with independent variables. The objective of the CGM is to find the minimum value of a function for unconstrained optimization problem and low memory usage (Alsuliman et al., 2020; Hamoda et al., 2015). The CGM is commonly solved by iterative method which is defined as follows:

$$x_{k+1} = x_k + \propto_k d_k, k = 1, 2, \ldots \quad (2)$$

Where $x_k$is the current iterative point, $\propto_k$is the step size (also known as the learning rate) and $d_k$is the search direction of conjugate gradient method. The step size can be solved in two ways the exact and the inexact line search. The search direction of conjugate gradient method d_k is defined as follows:

$$d_k = \begin{cases} -g_k & k=0 \\ -g_k + \beta_k d_{k-1} & k=1,2,\ldots \end{cases} \quad (3)$$

Where β_k is CG coefficient of $f(x)$ and $g_k$is the gradient at point x_k. $\beta_k \in R$ is a scalar while $g_k = \nabla f(x_k)$ at point x_k.

The conjugate gradient method has been modified severally by many researchers which we can find all the methods through (Hager and Zhang, 2005; Dolan and More, 2002; Powell, 1986; Andrei, 2008)

1. Hestenes-Stiefel (HS) method: this approach was first introduced by Hestenes-Stiefel in 1952 for solving linear CG method [Dia,2010], where the $\beta_k$is given as:

$$\beta_k^{HS} = \frac{g_k^T (g_k - g_{k-1})}{d_{k-1}^T (g_k - g_{k-1})} \quad (4)$$

   The drawback of this method is that it can only be used to solve linear equation [Duchi, 2011].

2. Fletcher-Reeves (FR) method: this was presented in 1964 by Fletcher and Reeves which proposed the first nonlinear CG method. CG parameter is as follows:

$$\beta_k^{FR} = \frac{g_k^T g_k}{\|g_{k-1}\|^2} \quad (5)$$

   The drawback of this method is that it may fall into some circles of tiny steps which may sometimes be very slow in practical computation to converge [Dai, 2010].

3. The Polak - Ribiere - Polyak (PRP) method: In 1969, Polak, Ribiere and Polyak proposed another conjugate gradient parameter which performs much better than the Fletcher-Reeves (FR) method for many optimization problems because it can recover automatically once small step is generated [Dai]. Where β_k is as follow:

$$\beta_k^{PR} = \frac{g_k^T (g_k - g_{k-1})}{\|g_{k-1}\|^2} \quad (6)$$

4. Kamfa*et al*., 2017 proposed (KMAR) conjugate gradient method:

$$\beta_k^{KMAR} = \frac{g_k^T (g_k - g_{k-1})}{g_{k-1}^T (g_k + g_{k-1})} \quad (7)$$

5. Sulaiman-Mustafa (SM1) conjugate gradient method: in 2018 [Sulaiman, 2018].

$$\beta_k^{SM1} = \frac{g_k^T \left(g_k - \frac{\|g_k\|}{\|g_{k-1}\|} d_{k-1} - d_{k-1} \right)}{d_{k-1}^T (g_k - g_{k-1})} \quad (8)$$

The main objectives of the study is to apply the FR conjugate gradient method to a predictive machine learning model and also to solve the problem(prediction of candidate's admission) within the shortest computation time with good convergence property.

Review of related work

This section provides a review of the relevant literature to the proposed work, these include previously proposed works on the prediction of the chances of student's enrolment in higher institutions of learning. There have been several extant works related to student's admission into universities. Previously proposed are multiple classification algorithms such as Decision Tree, Random Forest, Nave Bayes, and SVM were compared and evaluated based on their accuracy to select the best candidates for the college, and the Naive Bayes algorithm was used to predict the probability of an application's success. In Thi et al., (2007), Bayesian Networks were used to construct a decision support framework for evaluating international students' university applications. This model was created to predict prospective students' success by comparing them to the performance of students who were already enrolled in university and had a similar profile during their application. In this way, the model predicted whether or not the prospective student should be admitted to the university based on the current student profile. Due to the issue of class imbalance, the model proved to be less effective because the comparisons were only made with students who had already been admitted to the university and the data of students who had been refused admission was not included in the study.

Abdul Fatah and M (2012) proposed a model that can generate a list of universities/colleges that are the best fit for a student based on their academic records and college admission requirements. Their model was created by combining data mining techniques with knowledge based rules to improve the university's in-house admission prediction framework. Using the trend growth approach to association rule mining, Mane (2016) predicted a student's chance of getting into college based on their Senior Secondary School, Higher Secondary School, and Common Entrance Examination results. The models' result seems promising, but its limitation is that its focus was solely on a particular university.

A study from the perspective of estimating the probability of a student enrolling in the university after enquiring about courses was conducted by Mishra and Sahoo (2016).This study uses K-Means algorithm to cluster students based on various factors such as feedback, family income, family profession, parents' qualifications, motivation, and so on, in order to predict whether or not the student will enroll in university. The students were grouped into clusters based on how similar their attributes were for decisions to be taken. The goal of the model was to increase the number of students enrolled at the university.

Prediction of Admission Process for Gradational Studies using AI algorithm was proposed by Singhal and Sharma (2020). Graduate Admission Prediction (GAP), a method based on AI algorithms, was developed as part of the project. GAP is said to help students by predicting their chances of getting into Fantasy College. This paper compares and acknowledges which AI algorithm can produce the most accurate results. Conclusion were made that Random Forest is the most reliable algorithm for the dataset. The output of the college admission was predicted using machine learning techniques in a study conducted by Jamison (2017). The yield rate is the percentage of students who enroll in a course after being accepted by the university.

The model was created using multiple machine learning algorithms such as Random Forest, Logistic Regression, and SVM; the models were evaluated based on their efficiency and accuracy. The result shows that Random Forest outperformed the other models with 86% accuracy, and was thus used to build the method. The GRADE system was created by Waters and Miikkulainen (2014) to aid in the admission process for graduate students at the University of Texas' Department of Computer Science. The project's main goal was to create a framework that would assist the university's admissions committee in making better and quicker decisions. The model was built using both Logistic regression and SVM; both models performed equally well, and the final design was built using Logistic regression due to its simplicity. The time it took the admission committee to review the applications was reduced by 74%, but the final decision still needed human intervention.

Nandeshwar et al., 2014 developed a similar model to predict a student's university enrollment based on factors such as SAT score, GPA score, residency ethnicity, and so on. The model was developed using the Multiple Logistic Regression algorithm, and it only had a 67 percent accuracy rate.

MATERIALS AND METHODS

The conjugate gradient method is a first-order derivative optimization method related to first-order derivative optimization algorithms such as gradient descent and steepest descent. The efficiency of conjugate gradient is to find the minimum value for each parameter using the cost function. It is commonly done by iterative method which is defined as follows:

$$x_{k+1} = x_k + \alpha_k d_k \quad k = 1,2,\ldots \quad (9)$$

x_k is the current iterative point, α_k is step size (also called learning rate)

$$d_k = \begin{cases} -g_k, \wedge k = 0 \\ -g_k + \beta_k d_{k-1}, \wedge k \geq 1 \end{cases} \quad (10)$$

g_k is the gradient of the function at point k, β_k is the conjugate gradient coefficient for different conjugate gradient methods.

i. Algorithm

Conjugate gradient coefficient, β_k in FR method. Given the coefficient β_k as:

$$\beta_k^{FR} = \frac{g_k^T g_k}{\|g_{k-1}\|^2} \quad (11)$$

The algorithm is as follows:

Step 1: Initialization. Given x_0, set k=0.

Step 2: compute β_k based on β_k^{FR} as in (11).

Step 3: compute search direction d_k based on (10).

If $\|g_k\| = 0$, then stop, otherwise go to step 4.

Step 4: compute step size α_k

Step 5: update a new point by using (9)

Step 6: stopping criteria.

If $f(x+1) < f(x)$ and $\|g_k\| < \epsilon$, then stop.

Otherwise go to step 1 with k=k+1.

ii. Data Specification

The data used was collected from the admission office of The Gateway (ICT) Polytechnic Saapade for candidates seeking for admission in the institution for 2019/2020 admission session. The size of data set amounts to approximately 4150, that is 90% and 10% of the dataset for model's training and testing respectively.

Table1: Sample of dataset for training

Appnum	SexName	Age	State Name	PName	SessionName	JambNumber	JambScore	PUTMEScore	NoOfSittings	AdmiSSION
GTS1912706	MALE	19	ABIA	ACCOUNTANCY	2019/2020	96479912BJ	192	26	2	1
GTS1915164	FEMALE	17	ABIA	ACCOUNTANCY	2019/2020	96460260JG	173	26	2	1
GTS1919950	MALE	23	ABIA	ACCOUNTANCY	2019/2020	96655844JH	168	23	2	1
GTS1921099	FEMALE	21	ABIA	ACCOUNTANCY	2019/2020	96937039CE	186	21	1	1
GTS1920264	FEMALE	22	AKWA-IBOM	ACCOUNTANCY	2019/2020	95137630AH	182	19	1	1
GTS1918711	MALE	24	AKWA-IBOM	ACCOUNTANCY	2019/2020	96590011AH	165	32	1	1
GTS1915094	FEMALE	21	AKWA-IBOM	ACCOUNTANCY	2019/2020	96400526EC	172	25	1	1
GTS1915576	FEMALE	22	AKWA-IBOM	ACCOUNTANCY	2019/2020	99999999AA	150	28	2	1
GTS191	MALE	23	AKW	ACCOUN	2019/202	96936124	188	30	1	1

6734			A-IBOM	TANCY	0	FD				
GTS1919901	FEMALE	20	ANAMBRA	ACCOUNTANCY	2019/2020	96527252AH	201	25	1	1
GTS1920829	MALE	24	BENUE	ACCOUNTANCY	2019/2020	96911414HF	186	18	1	1
GTS1915872	MALE	24	BENUE	ACCOUNTANCY	2019/2020	96910259EI	169	27	1	1
: .										

iii. Normalization of Data Collected

Studying the data, the input variables have dynamic range which differ by orders of magnitude and thus suggest that a suitable normalization should be applied so that the transformed variables all cover the same range. In this research, the linear scaling transformation and was used to normalize the collected data.

Method: linear scaling transformation is a linear transformation applied to each input variable x_i independently was used. In this method, min) which is the minimum of data x and $max\left(x_i\right)$ are calculated as:

$$z_i=\frac{x_i-min\left(x\right)}{max\left(x\right)-min\left(x\right)} \qquad (12)$$

Where $x=\left(x_1,x_2,\ldots,x_n\right)$ and z_i is now your i^{th}normalized data

iv. Formulation of the Model

The logistic regression analysis will be carried out by using UTME SCORE (x_1), POST-UTME SCORE (x_2) data as independent variable and ADMISSION (y) data as dependent variable.

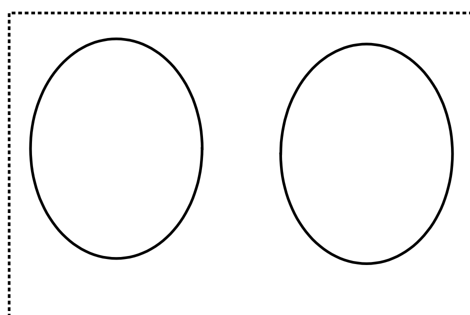

Figure 1: neural network representation of the problem

Hypothesis: $net=\beta^T x=x_0\beta_0+\beta_1 x_1+\beta_2 x_2 \, where \, x_0=1 \left(13\right)$

$$h_\beta\left(x\right)=f\left(net\right) where\ the\ function\ f\ is\ \log-Sigmoid\ activation\ function$$

$$h_\beta\left(x\right)=\frac{1}{1+e^{-net}}\left(14\right)$$

Parameters: $\beta=\beta_0,\beta_1,\beta_2$

Cost function: $$J(\theta)=\frac{1}{m}\left[\sum_{i=1}^{m}-y^{i}\log\left(h\theta\left(x^{i}\right)\right)+\left(1-y^{i}\right)\log\left(1-h\theta\left(x^{i}\right)\right)\right] \quad (15)$$

To evaluate the performance of the method in comparison with gradient descent method, we employ fletcher-reeves (FR) conjugate gradient methods.

RESULTS AND DISCUSSION

i. System Requirement

All experiments were implemented on a PC with theHardware configuration of PC workstation with Intel® Core™ i5-5020U CPU @ 2.20GHz, 8GB of RAM; and Python is the main programming language that is used to implement this study. This is due to the availability of vast amount of open source python-based libraries and packages. The major libraries and packages used include:

i. Numpy: for array processing. It provides good support for different dimensional array objects as well as for matrices.
ii. Pandas: for manipulate any type of data
iii. Matplotlib: for 2-dimensional graphs and plots
iv. Time: for time-related functions.

The Results

Figure 2is an excerpted from the results generated after running the FR algorithm showing values of the parameters ($\beta=\left[\beta_0,\beta_1,\beta_2\right]$), the objective function value at each iteration, the numbers of iteration and the total runtime taken for the algorithm to reach the optimal value of the objective function.

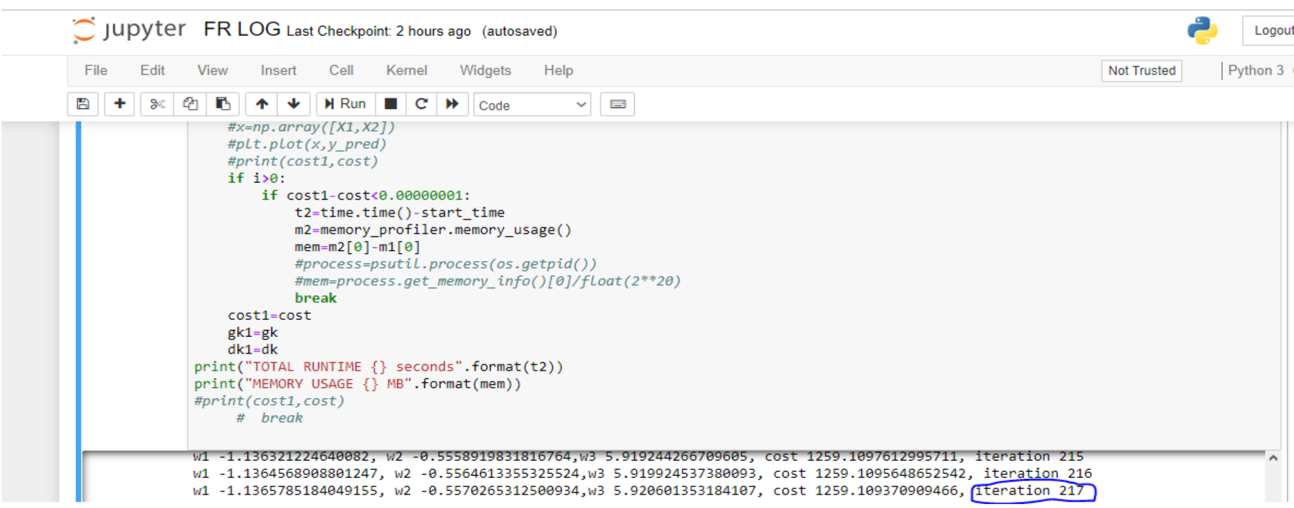

Figure 2: Results of fletcher-reeves (FR) conjugate gradient method in Python

Numerical Results and Discussion

In this section, our application of fletcher-reeves (FR) conjugate gradient method in comparison with Gradient descent method is explained.For the problem, five experiments was performed with the same initial guess in order to evaluate the efficiency of the method. The stop criteria used in the experiment for both algorithms, convergence is assumed if $\|g_k\|\leq\varepsilon$ where $\varepsilon=10^{-3}$. The initial point for the parameters $\beta_0,\beta_1,\beta_2$are (0,0,0) and the learn rate $\propto=0.0001$

Table 2: Performance table for the problem

S/N	Methods	Number of iteration	Processing time (m)	Optimal values	$\beta_0, \beta_1, \beta_2$
1	fletcher-reeves (FR)	217	1.127	1259.1093	(-1.137, -0.557, 5.921)
2	gradient descent method	3822	18.979	1426.8432	(-1.184, -0.512, 5.926)

Table 2 shows the results for fletcher-reeves algorithms and gradient descent algorithms respectively. The numerical results indicates that fletcher-reeves algorithms made significant performance among both algorithms. The performance from implementation of problem indicates that the Fletcher-Reeves (FR) method outperformance the gradient algorithms both in terms of number of iteration and process response time.

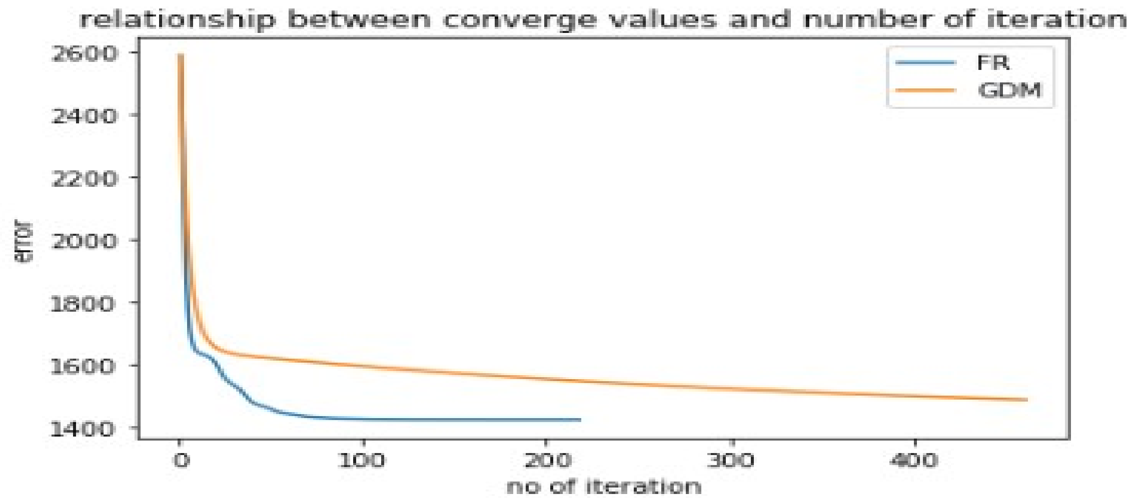

Figure 3: The performance results based on number of iteration.

From the figure 3, we can see that the lower curves are referring to FR methods. This shows that the method performs better than GD method based on number of iterations prior to reachingthe optimal values (minimum cost).

Accuracy test

From the result presented in table 2, we find that the fletcher-reeves (FR) conjugate gradient method is a good and fit model that can be use to predict the category our dependent variable.

Hypothesis: $net = x_0 \beta_0 + \beta_1 x_1 + \beta_2 x_2 \; where \; x_0 = 1 \; (16)$

The parameters $\beta_0, \beta_1, \beta_2 = ¿$(-1.137, -0.557, 5.921) respectively which can be fit into (16) to be use for prediction.

Therefore we have,

$$net = -1.137 - 0.557\,x_1 + 5.921\,x_2 \quad (17)$$

$h_\beta(x) = f(net)$ *where the function f is* $\log - $ *Sigmoid activation function* from equation (14):

$$h_\beta(x) = \frac{1}{1 + e^{-net}} \quad (18)$$

Meanwhile, the equation (18) is used for testing the model and the result is as shown in Table 3.

Table 3: Sample of testing result

S/N	JambScore	PUTMEScore	AdminInfo	y_pred
1	194	28	1	1
2	172	24	1	1
3	180	15	1	1
4	182	16	1	1
5	185	24	1	1
6	172	18	1	1
7	188	0	0	0
8	179	24	1	1
9	169	25	1	1
10	191	27	1	1
: :	: :	: :	: :	: :
408	148	30	1	1
409	164	14	1	1
410	180	20	1	1
411	152	12	1	1
412	169	12	0	1
413	161	0	0	0
414	165	19	1	1
415	151	23	1	1

Sample: from (17)

$$net = -1.137 - 0.557\,x_1 + 5.921\,x_2$$

x_1 represents the JambScore and x_2 represent the PUTMEScore. Using the dataset 1 as an example, so x_1=194 and x_2=28

$$net = -1.137 - 0.557(194) + 5.921(28)$$

$$net = 56.593$$

Using (18)

$$h_\beta(x) = \frac{1}{1+e^{-net}} = \frac{1}{1+e^{-56.593}} = 1$$

Therefore, the result indicate admitted. Similarly to other test dataset.

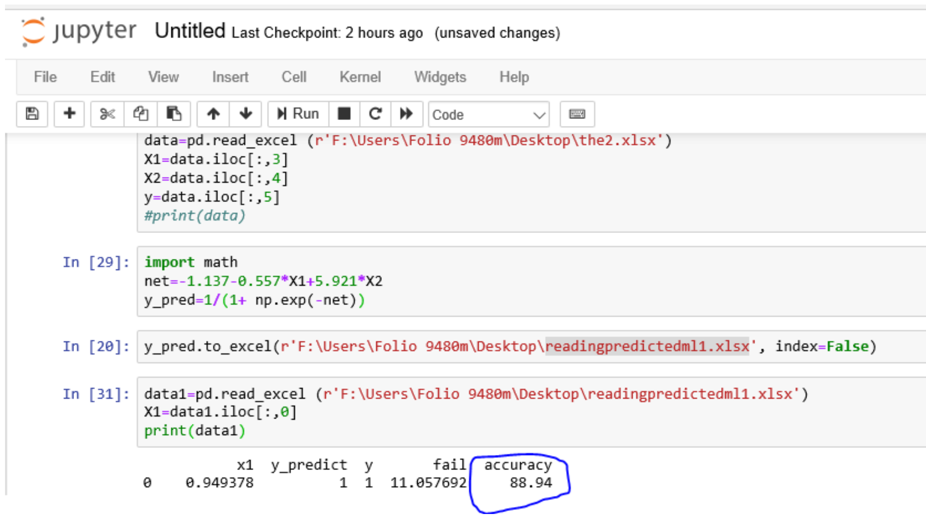

Figure 3: result of accuracy of the model

In figure 3, the output of the fletcher-reeves (FR) conjugate gradient method gives 88.94% prediction accuracy.

CONCLUSION

This research work presented an overview of applying Conjugate Gradient Method as an optimization model using a single neuron network with the sigmoid activation function which is used to predict whether the candidates who applied for an admission into The Gateway (ICT) Polytechnic Saapade is admitted or not using his/her UTME score and POST-UTME score. Furthermore, the Fletcher-Reeves (FR) conjugate gradient method performs better than the gradient method given the number of iteration and processing time.

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