Development of a Biometric Based Employment Tracking System (ETS) Using Machine Learning Approach

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DOI: https://doi.org/10.51584/IJRIAS.2025.10060056

Received: 31 May 2025; Accepted: 04 June 2025; Published: 08 July 2025

ABSTRACT

This study presents the development, implementation, and validation of two intelligent systems: an Unemployment Prediction Model and an Employment Tracking System (ETS), aimed at enhancing workforce planning and mitigating employment fraud in Nigeria. The unemployment prediction model was developed using linear regression and Feed Forward Neural Network (FFNN) techniques, trained on NYSC data of higher education graduates over five years. The ETS was developed using an FFNN classification model trained on fingerprint data from the Federal Ministry of Labour, Employment, and Productivity (FMLEP). The model was evaluated using Mean Square Error (MSE), Receiver Operating Characteristics (ROC), and confusion matrix andthe system implementation result achieved an average classification accuracy of 97.16% and a ROC of 0.9777, indicating a high capability in accurately detecting employed individuals. Initial results from the linear regression model showed a regression value (R^2) of 0.88 but suffered from high Root Mean Square Error (RMSE), indicating poor reliability. Consequently, the FFNN was reconfigured for regression using a neural network time series application, resulting in improved performance with a regression value of 0.99624 and a near-zero RMSE of 0.050165. Validation through tenfold cross-validation confirmed the robustness of both models, with the FFNN outperforming linear regression by 20.4% in prediction accuracy. Furthermore, integration of the ETS enabled real-time identification of previously employed individuals through fingerprint matching, effectively preventing multiple government job applications using fraudulent identities. The results from the system demonstrated that FFNN-based models offer superior performance in both predictive and classification tasks within employment analytics. The integration of these systems into labour market governance provides a promising approach to data-driven decision-making, fraud prevention, and enhanced workforce transparency.

Keywords: Employment Tracking System (ETS); Feed Forward Neural Network (FFNN); Unemployment Prediction; Regression Analysis; Fraud Detection

INTRODUCTION

Unemployment has remained a persistent global challenge, drawing significant research interest due to its complex and multifaceted nature. In Nigeria, numerous efforts have been made to address this issue using technological interventions (Bello, 2003; Adesegun et al., 2020; Etuk & Onwuachu, 2016). Biometric technologies, particularly fingerprint systems, have proven effective for employment tracking and have been employed by researchers to help mitigate unemployment. Similarly, artificial intelligence techniques, including time series forecasting models, have been used to predict unemployment trends and guide policy responses.

This study explores the integration of the Digital Nervous System (DNS) a biometric and data-driven framework alongside other technological tools, such as employment tracking systems, as innovative approaches to addressing unemployment in Nigeria. While successive Nigerian governments have introduced various initiatives to curb unemployment, including the National Directorate of Employment (NDE), National Poverty Eradication Programme (NAPEP), Poverty Alleviation Programme (PAP), and Subsidy Reinvestment and Empowerment Programme (SURE-P), these efforts have often failed to achieve their intended impact (Ekpo, 2008).

Despite reported real GDP growth rates of 6–6.5% since 2005 (Damachi, 2011), unemployment has continued to rise from 12.1% in 2016 to 27.1% in 2021 (Olorunfemi, 2021) highlighting a paradox of jobless growth. Prior studies, such as Gil-Alana (2001), attempted to model unemployment using the exponential Bloomfield spectral model, achieving modest results. However, performance can be improved through the application of machine learning and employment tracking technologies.

It is important to distinguish between employment tracking systems and employee tracking systems. The former identifies an individual's employment status using biometric or physiological data, while the latter monitors an employee's activities during their period of employment (Adewole et al., 2014; Eromosele, 2016; Talaviya et al., 2013; Harbor et al., 2021).

Despite the presence of intervention agencies, issues like ghost workers and multiple employment frauds persist both considered criminal offenses under Nigerian law. Addressing unemployment in Nigeria requires a holistic strategy that tackles root causes and includes accurate data planning, verification of current employment records, and the creation of new opportunities.

This research proposes a Digital Nervous System-based Unemployment Management System that integrates biometric verification to track employment status. It uses physiological traits to identify and confirm employed individuals and helps detect fraudulent employment claims. Additionally, a machine learning-based regression model was developed to forecast unemployment trends specifically, the number of unemployed graduates from Higher Education Institutions (HEIs) over the next ten years. Trained using data from federal agencies, this model supports government planning by providing accurate predictions to guide policy and resource allocation.

METHODOLOGY

Research methodology and systems development methodologies were used in this study. Development of a system that can effectively track the employed and unemployed HEIs graduates was achieved using fingerprint technology and feed forward neural network. Linear regression techniques were used to effectively predict unemployment status. The FMLEP at every state as well as the NYSC database were digitally linked via internet. The new system was analysed using Object Oriented Analysis and Design Methodology (OOADM). The reason was because of its ability to balance emphasis between process and data; using universal modelling diagrams to describe the system concepts and achieve quality system structure (Ajah and Ugah, 2013).

Data collection and data processing

The biological information collected from FMLEP and the data collected from NYSC were structured and required no special attention in for purification due to the data arrangements. However, in the case of the biometric data collected which is fingerprint, many limitations affected the original data such as noise and poor visualization, arising from the data acquisition hardware. Hence there was need for data filtering and also data enhancement.To filter the noise attributes on the fingerprint such as the salt and pepper noise, speckle noise, Gaussian noise, etc, the median filter recommended by Ruchika and Guarav (2013) was adopted. The reason this nonlinear filter was used ahead of linear filters was due to its ability to remove noise and preserve edges on the image which is vital for reliable fingerprint verification result (Subba et al., 2018). The median filter identified the pixels of the fingerprint data collected and then replace it with the median value of the neighbouring pixels from the same image. This ensured that the output was the average element of the sorted pixels for each fingerprint data and quality fingerprint output with preserved finger ridges were produced.

Having processed the fingerprint, the need for image enhancement wss vital to better reveal the ridges of the fingerprint and compensate for the limitation of the image acquisition device (DIP, 2007). This was achieved using histogram equalization technique. This approach is versatile in image processing problems and is very effective for enhancement of the image resolutions. This histogram equalization process is a nonlinear contrast enhancement solution which is very compatible with the adopted median filter to process further the fingerprint. In this case the approaches retransformed the fingerprint data and produced a uniform population density via the clustering of adjacent grey values which brightened the image and improved the image quality, especially when the histogram was at the peak.

Modelling of the Digital Nervous System

The present solution to unemployment seeks to solve the problem where one person holds multiple job positions, in many cases, with different names as ghost workers, or in other cases with real names so as to exploit the government and earn two or more salaries. It is very unfortunate that today key positions at the government MDAs are not advertised because these job slots are shared among the political elites, usually for their cronies, some of who are already employed.This has remained a major cause of unemployment in Nigeria.

To address this problem the ETS was developed which uses biometric information of every person seeking employment with the FMLEP to search and classify if such a person is already in active service or not. The future solution also seeks to first establish a model of the number of expected higher education graduates via NYSC using the linear regression model of unemployment. The Use Case of the digital nervous system gives a user point of view of the system with different users referred to as the actors such as the job seekers and government, while the supporting actor is the FMLEP. Figure 1 shows the Use Case for the unemployment prediction system.

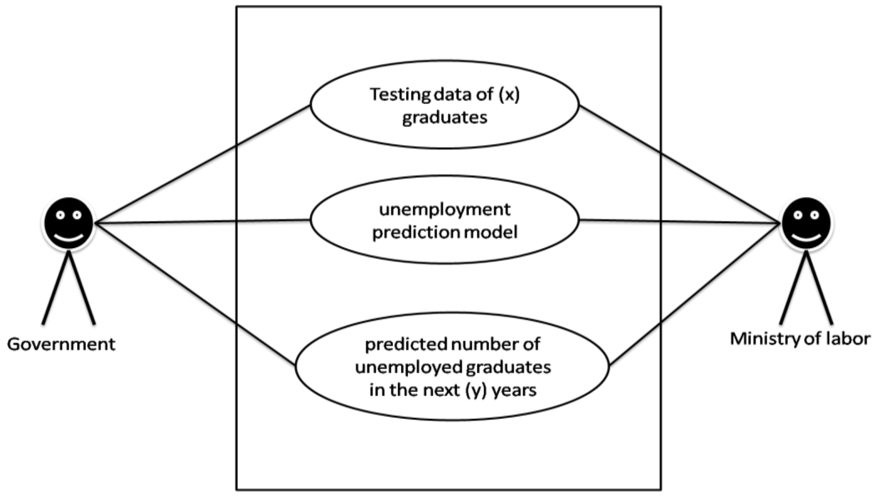

Figure 1: Use case for unemployment prediction system

Primary actors**:** Government

Secondary actors: Federal Ministry of labour, Employment and Productivity (FMLEP)

Brief description of event: The government uses the unemployment prediction model to estimate the number of expected NYSC members in the future (Figure1) and then submits the data to the FMLEP.

Pre-conditions: We assumed that the past (x) data of the NYSC graduates were already loaded into the system for training and prediction.

Post-conditions: The information obtained from the prediction will help the government and the FMLEP in planning.

Main flow of events

1. Testing data of past NYSC graduates
2. Unemployment prediction model
3. Predicting the number of NYSC graduates in future

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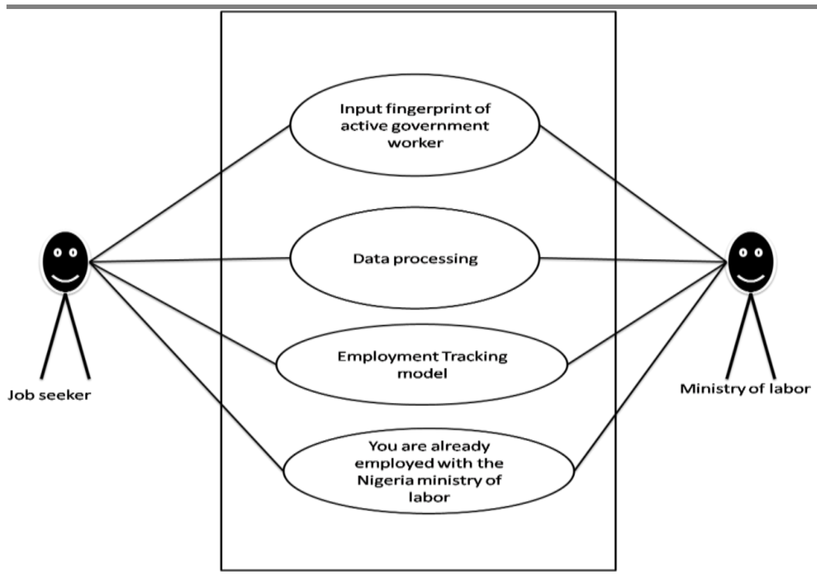

Figure 2. Use Case of the ETS for employment fraud detection

Primary actors**:** Job seeker

Secondary actors**:** Federal Ministry of labour, Employment and Productivity (FMLEP)

Brief description of event: Here the job seeker who is already an existing employee of the government MDA wants to apply for another government job. When the finger print was inputted into the system, the employment tracking model developed could classify the person as an already existing government employee (Figure 2).

Pre-conditions: We assumed that the person applying for the job is already a full-time employee of the federal government.

Post-conditions: The person identified as already employed is disqualified for the new job recruitment.

Main flow of events

1. Input fingerprint ID
2. Data processing
3. Classification model for employment tracking
4. Results of classification

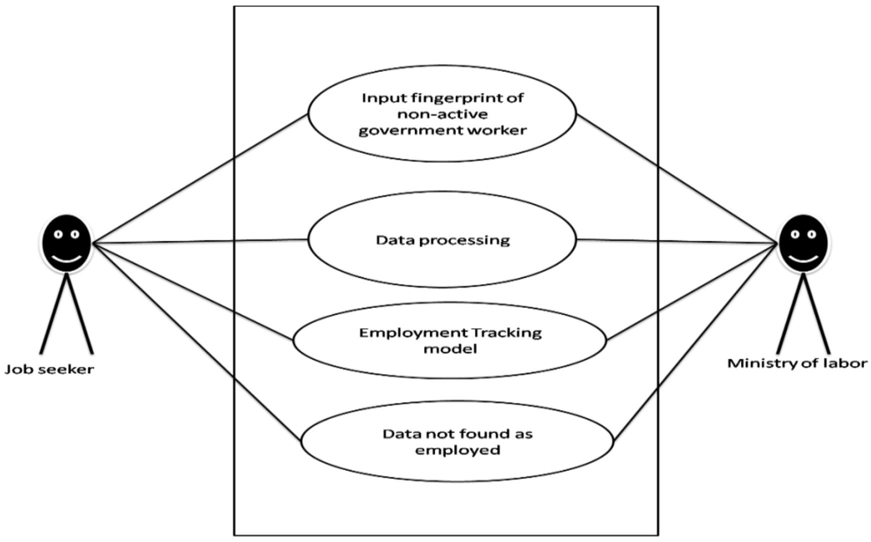

Figure 3. Use Case of ETS for identifying non employed persons

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Primary actors**:** Job seeker

Secondary actors**:** Ministry of labour, Employment and Productivity (FMLEP)

Brief description of event:Here the job seeker which is a new NYSC graduate inputs fingerprint to apply for a job. The classification model trained and classified the data as "not found" (Figure 3) with the FMLEP dataset and hence eligible for employment.

Pre-conditions: We assumed that the person applying for the job has already completed his/her NYSC but has not secured employment with the government.

Post-conditions: The person identified as "data not found" with the FMLEP is considered for employment.

Main flow of events

1. Input fingerprint ID
2. Data processing
3. Classification model for employment racking
4. Results of classification

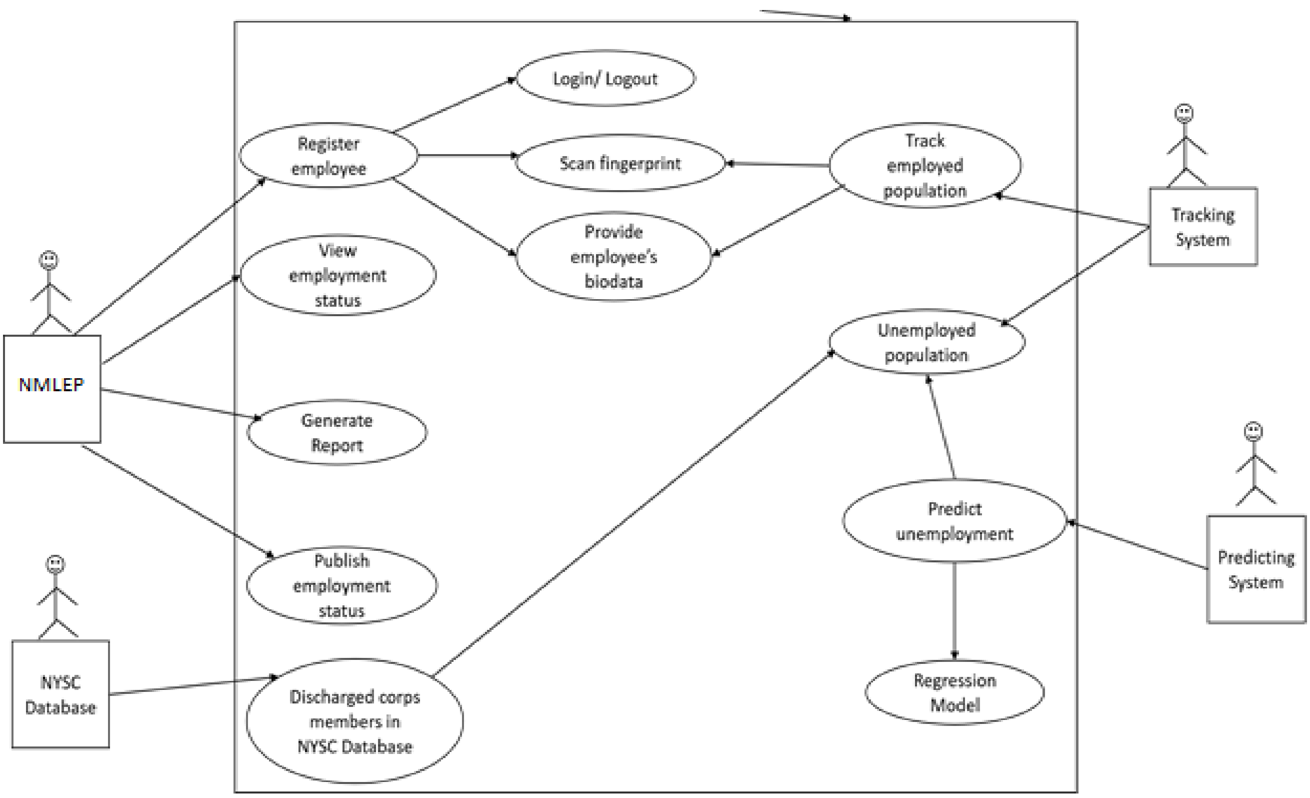

Figure 4: Use Case of the digital nervous system

Primary actors**:** FMELP and NYSC database

Secondary actors**:** Tracking system and Prediction system

Brief description of event:Data of employees of Federal Ministries, Departments and Agencies (FMDAs) were collected from FMELP, both biometric and biological, and then scanned to generate report of their employment status(Figure 4). The tracking system could track the employment status of workers, using their fingerprint scan. The prediction system on the other hand was used to predict the unemployment figure using the data of discharged NYSC members.

Pre-conditions: We assumed that the person applying for the job has already completed his/her NYSC and also all data of the FMELP are already recorded into the system.

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Post-conditions: The person identified as "data not found" with the FMLEP is considered for employment, while those "found" are identified as already employed.

Main flow of events

1. Registration of employees
2. View employment status
3. Generate report and publish
4. NYSC discharge members
5. Tracking system
6. Track employment population
7. Prediction system
8. Regression model
9. Unemployment prediction

Sequence Diagram

The sequence diagram was used to model the process of interaction in time series of the digital nervous system developed. The sequence diagram for the EST isshown in Figure 5 with the objects such as biometric verification, data processing, classification and final results.

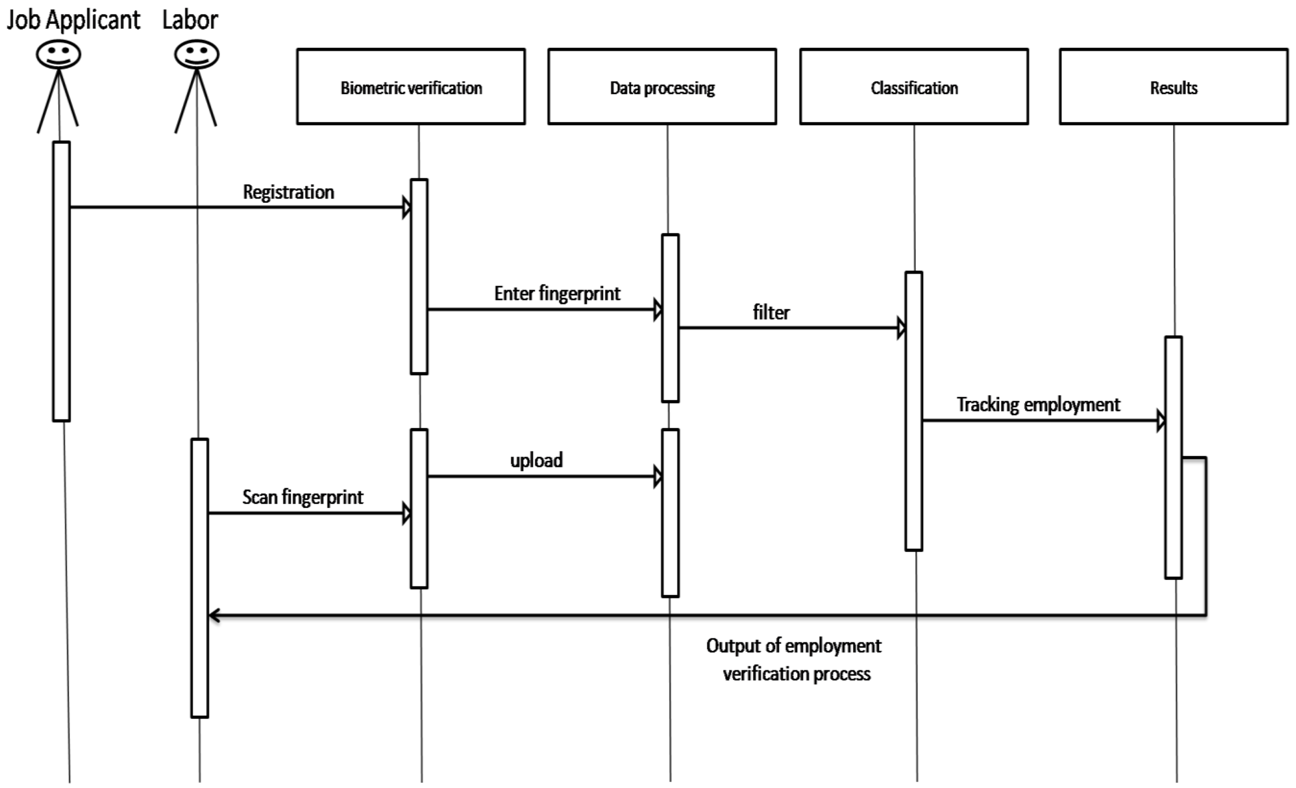

Figure 5. Sequence diagram of the employment tracking system

The applicant applies for the job via registration of biometric and biological information. The data are processed and then classified using the ETS model to determine if the person is already employed with the FMLEP or not.

The sequence diagram of Figure 6 was used to model the interaction between the objects during the prediction of unemployed graduates in time series. The objects in this case are the data upload (data collection), unemployment prediction model, output of the prediction, creation of employment. The data of dependent variables which is the NYSC number of the discharged corps members were collected and uploaded into the unemployment prediction model. This output information can be used to plan and create jobs for the citizens by the government.

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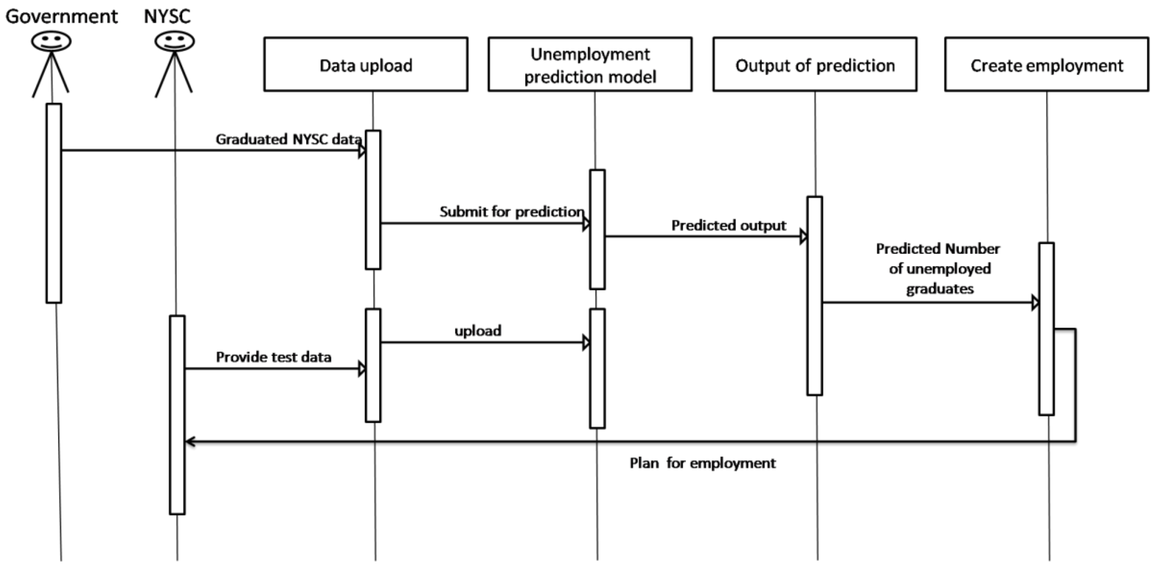

Figure 6: Sequence diagram of the unemployment prediction model

System Implementation

The system was implemented with Simulink. The unemployment prediction model was generated using regression application software in MATLAB while the ETS was generated using the neural network application software. The regression application software was loaded with the data and then trained using the linear regression model to generate the result of the unemployment prediction model which was exported and used for time series prediction of the NYSC corps members from the Nigerian approved HEIs. Figure 7shows when the data was loaded into the linear regression model for training.

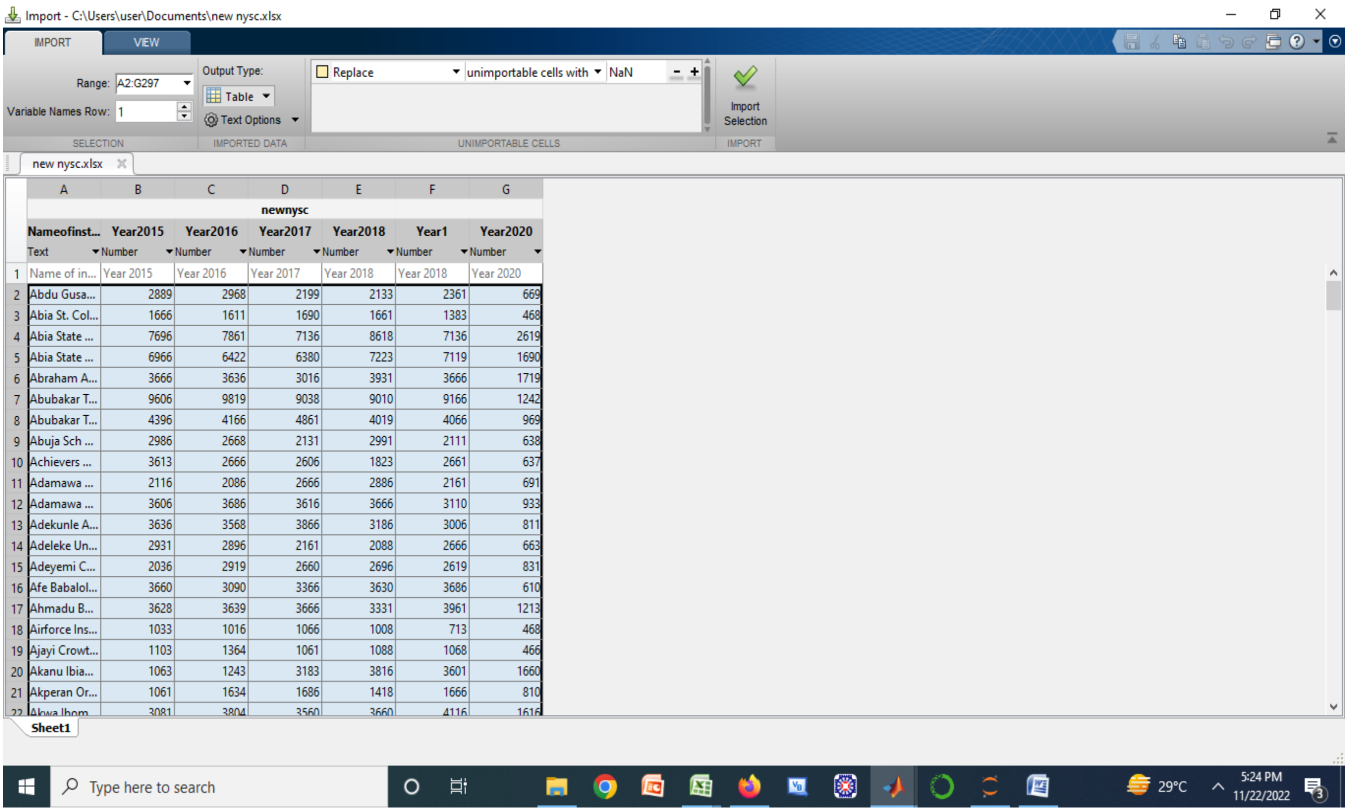

Figure 7: Regression learner application software for loading the data

The NYSC data were uploaded into the tool and the linear regression model developed was used to train the data. Figure 8 presents the scattered plots of the actual data which is the dependent variable that was trained to generate the prediction model.

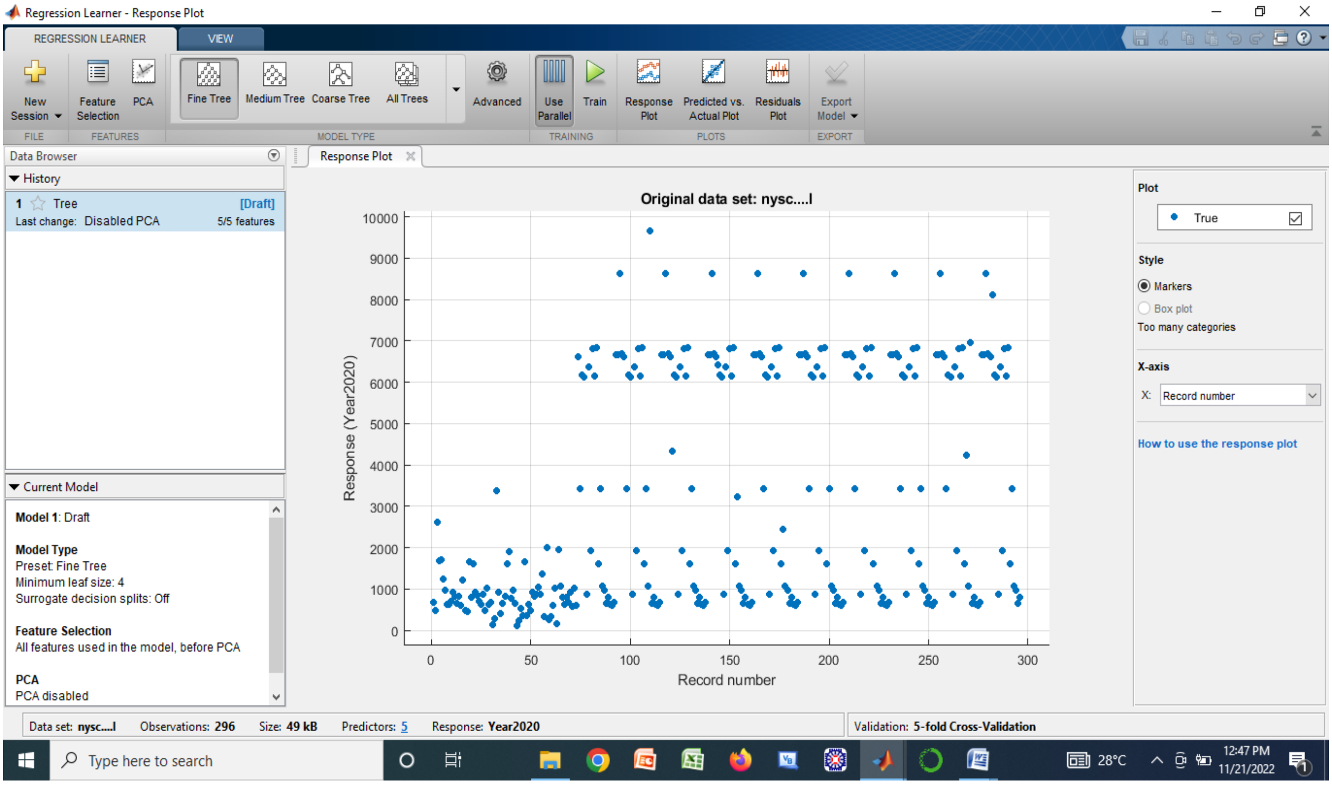

Figure 8: Regression learning application software for data training

Figure 8 presents the data points which represents the actual number of NYSC list produced from the 297 approved HEIs. These data were trained using the linear regression model developed to generate an unemployment prediction model. The ETS was also developed using the neural network application software in MATLAB as shown in Figure 9.

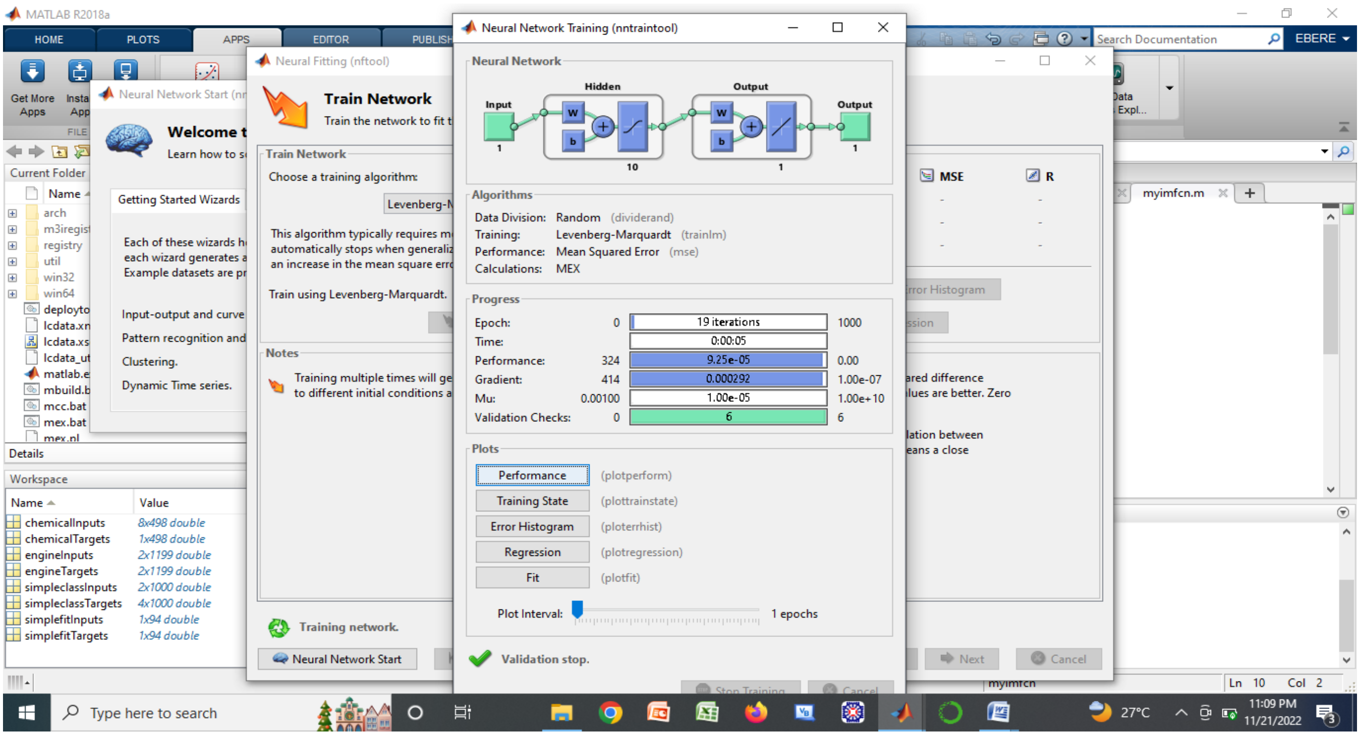

Figure 9: The neural network pattern recognition software for training of the fingerprint data

Figure 9 presents the neural network tool which was loaded with the fingerprint data and then trained. Before the training, the data loaded were automatically divided into training, test and validation sets and then trained using back propagation as shown in Figure 10.

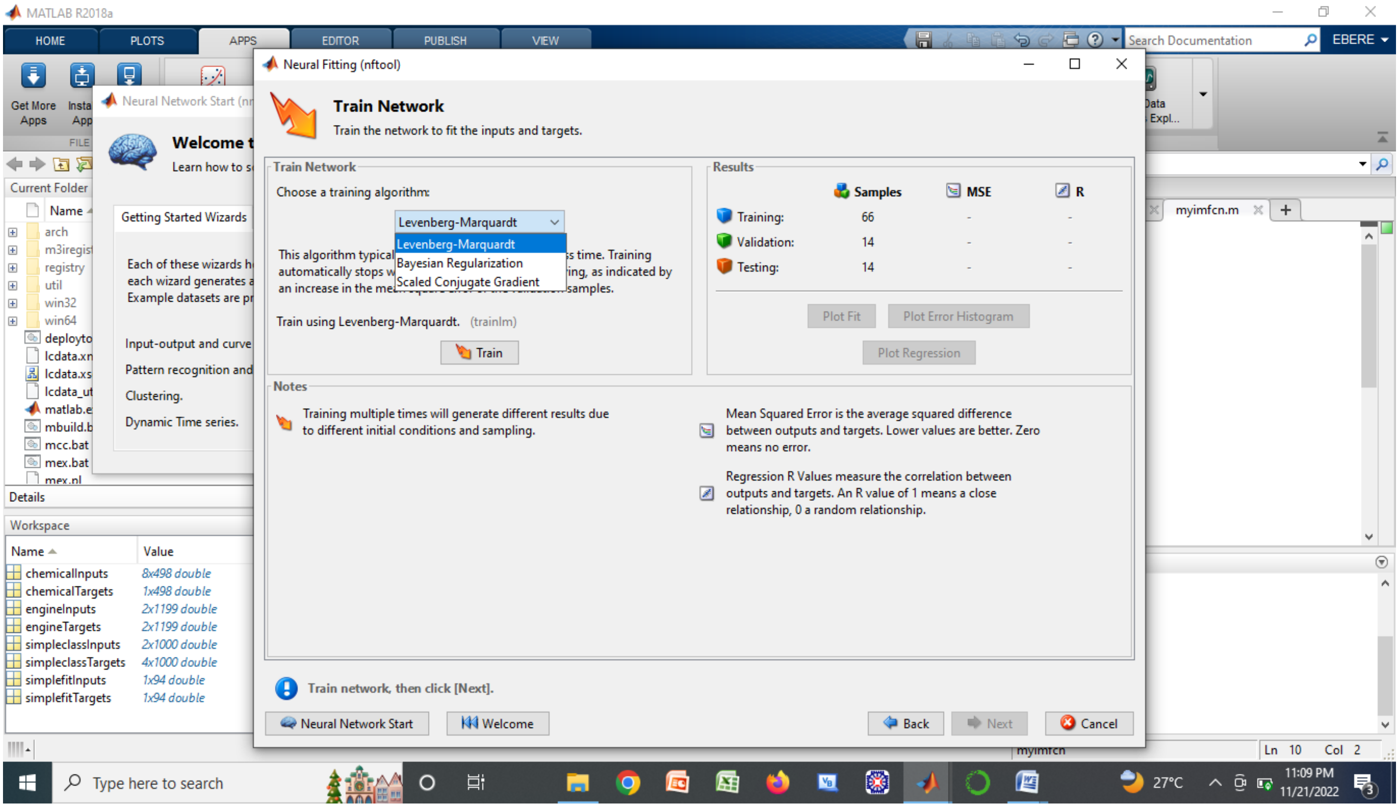

Figure 10: Neural network training with back-propagation algorithm

The training adjusted the weights of the neurons until the error between the training data and the target values was minimal. During the training process, the error was examined at each epoch and if not minimal, the output of the training was feedback (back-propagation) to the neuron input and then the training continued. At the epoch when the error was minimal, the performance was validated and then the training automatically stopped and generated the desired classification model for ETS. The implementation of the ETS is as shown in Figure 11.

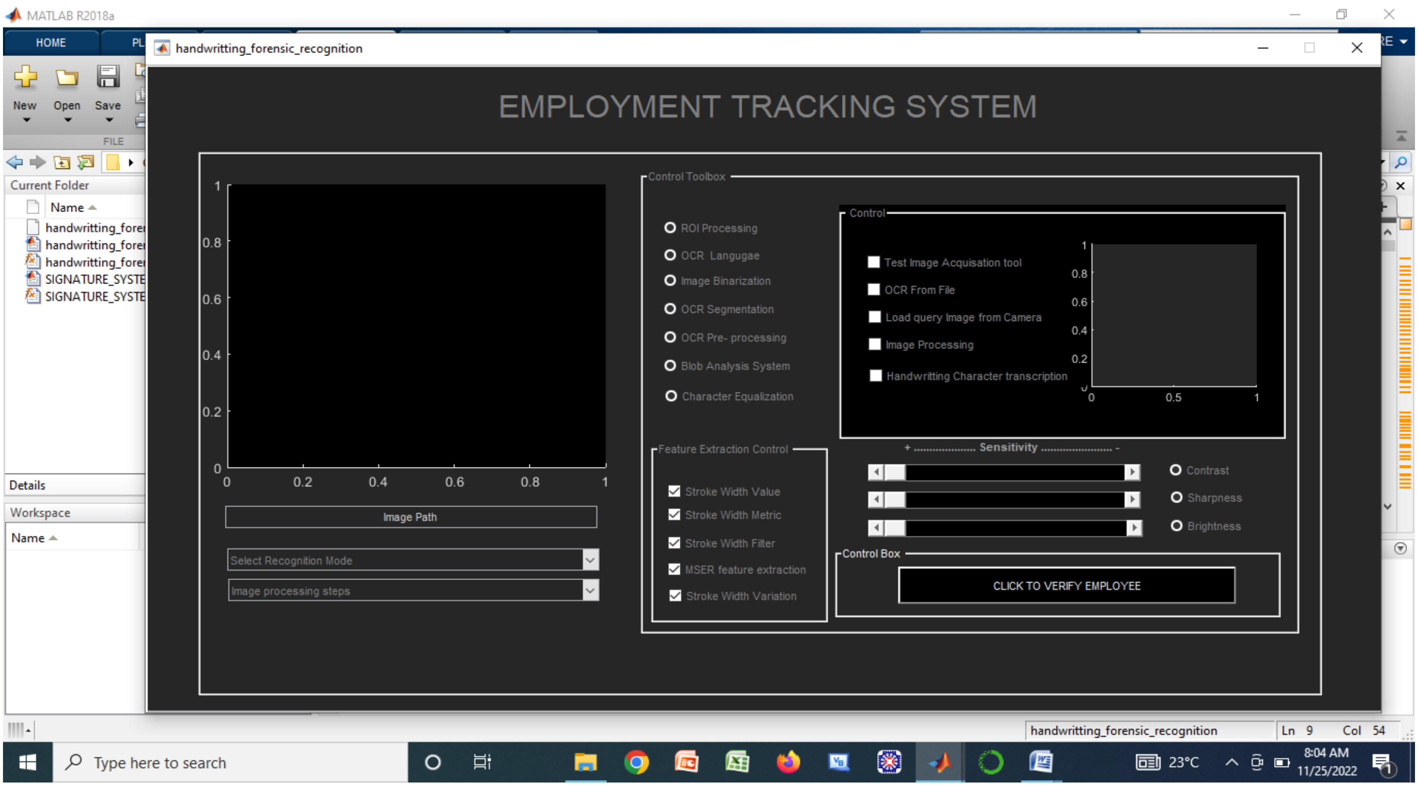

Figure 11: The employment tracking system

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The system was developed using the ETS model generated from the FFNN training as an expert system to solve the problem of employment fraud. Table 1 shows the training parameters of the neural network.

Table 1. Configuration data of the FFNN

Training Parameters	**Values for ETS**	**Values for prediction model**
Maximum number of epoch to train	18.0	8.0
Epoch between display	1.0	1.0
Maximum time to train in sec	Infinity	Infinity
Validation check	6	6
Initial step size	0.01	0.01
Minimum performance gradient	1.0×10^{-6}	1.0×10^{-6}
Cost horizon	7	7
Control horizon	2	2
Number of bias function	297	9
Training Iterations	76	76
Number of hidden layers	310	16
Number of weights	60	60
Number of input class	297	9

RESULT OF THE ETS MODEL IMPLEMENTATION

Before the performance evaluation of the FFNN for ETS, it has to be established that the FFNN can be used to generate both classification and regression models. This was achieved based on the training tool, as the neural network time series application software was used for the generation of the prediction model while the neural network pattern recognition application software was used to generate the classification model to be evaluated in this section. The performance of the classification model generated for the ETS was evaluated using receiver operator characteristics curve, confusion matrix, area under curve and MSE (Figure 12).

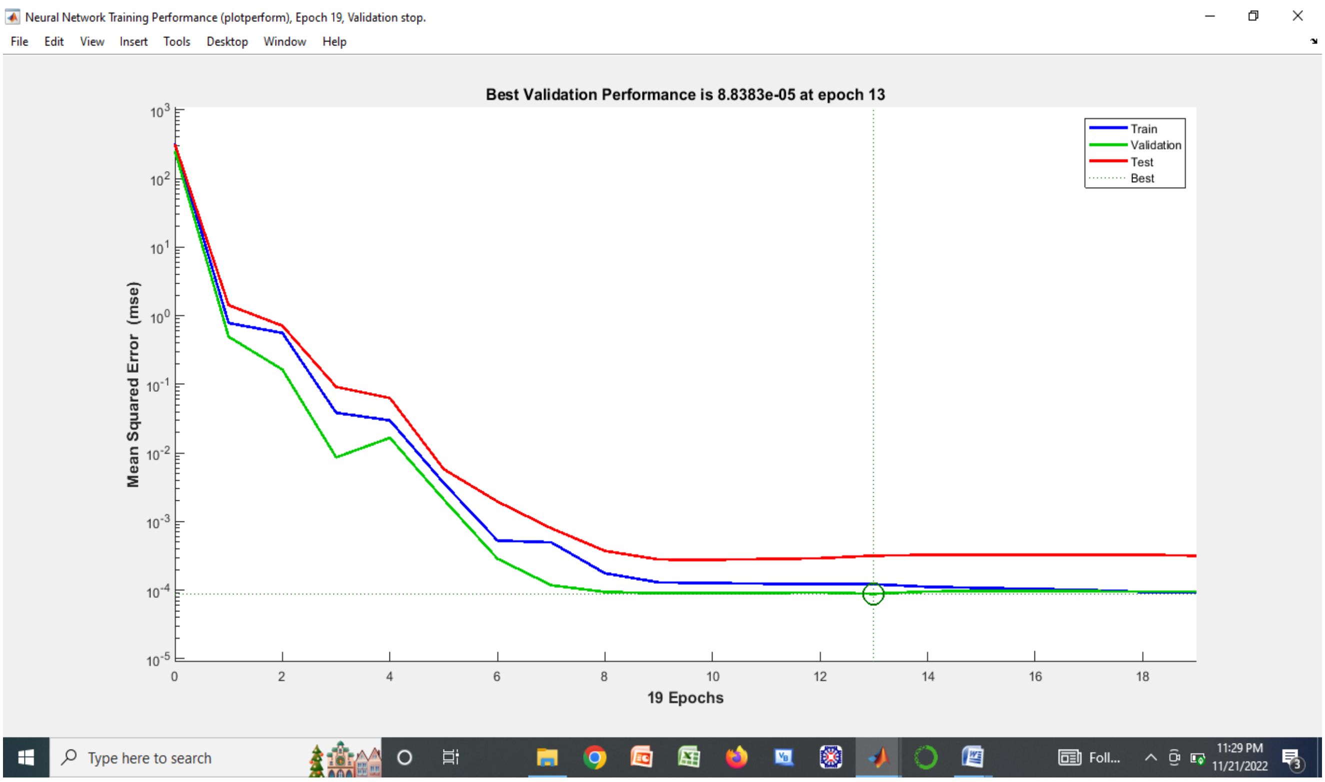

Figure 12: MSE performance of the ETS

Figure 12 shows the MSE performance of the ETS model which was trained using FFNN. The result showed that at epoch13 the best MSE performance was achieved as 8.838e-05Mu. The implication of the result is that

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the error which occurred during the training of the FFNN neurons was approximately zero, which implies good training performance. The receiver operator result of the classification model which was used to show the relationship between true classification and true negative classification is as shown in Figure 13.

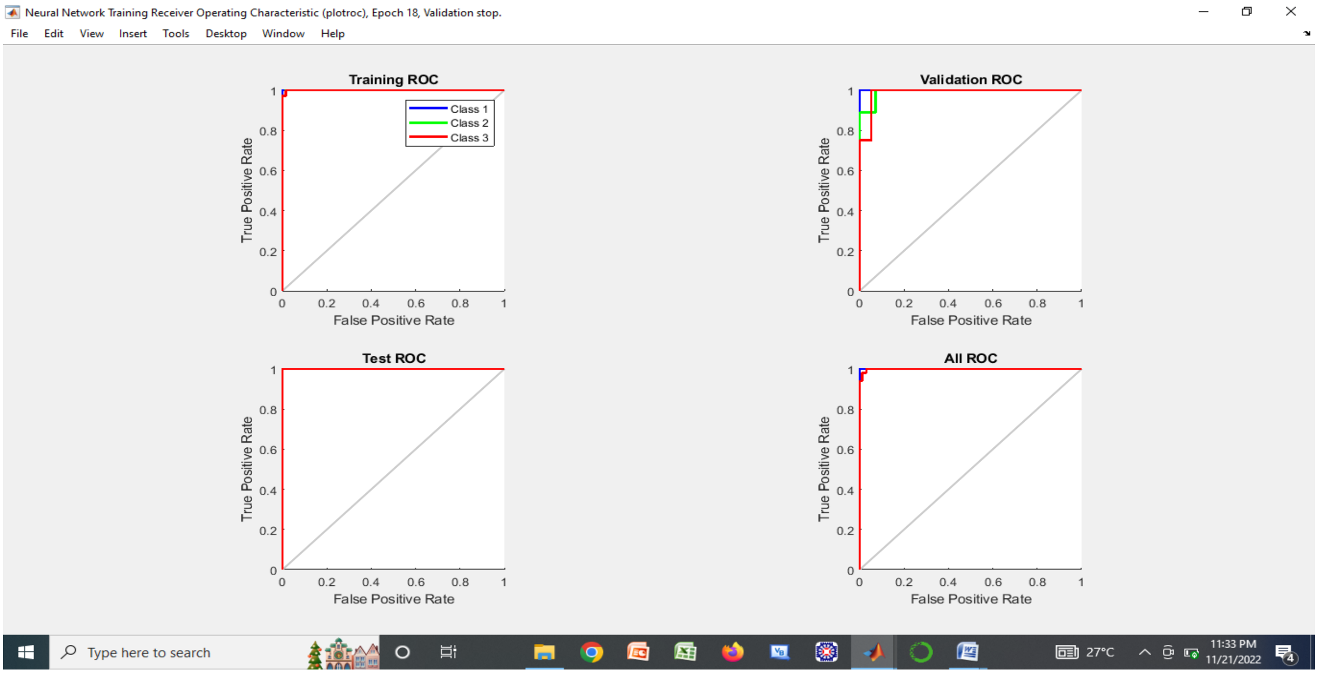

Figure 13: Receiver operator characteristics (ROC) result of the ETS model

Figure 13 shows the ROC of the ETS model which indicates the overall average area under the curve to be 0.987. This implies that the ETS model will correctly classify the staff of FMLEP as “employed” when they apply for another government job. The result also shows that the model will correctly classify non staff of FMLEP as“not employed”.

Figure 14: Classification performance using confusion matrix

Figure 14 shows the confusion matrix of the ETS model which was used to evaluate the accuracy of classification between the training, test and validation sets. The result shows that the average accuracy

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achieved with the ETS model is 96.7% for correct classification of fully employed staff of FMLEP seeking for multiple government employment. The result also achieved overall false classification of 1.3% which is tolerable as it is minimal.

Validation of Results

The results of the models developed for the ETS and also for the unemployment prediction were also validated. The approach used for the validation was the tenfold cross validation technique and the parameters considered for the validation were the performance evaluation index used to analyze the performance of the respective models.The validation of the unemployment prediction model is presented in Table 2.

Table 2: Validation of the unemployment prediction model

S/N	Feed forward neural network			Linear regression model		
	Regression	MSE	RMSE	Regression	MSE	RMSE
1	0.99	0.00251	0.05017	0.88	0.0000958	978.06
2	0.97	0.00265	0.05543	0.76	0.0000656	545.06
3	0.98	0.00564	0.06567	0.76	0.0000745	355.06
4	0.98	0.00446	0.05066	0.67	0.0000756	345.06
5	0.97	0.00767	0.06455	0.88	0.0000935	975.06
6	0.98	0.00353	0.04234	0.88	0.0000977	545.06
7	0.99	0.00734	0.04656	0.69	0.0000454	954.06
8	0.99	0.00745	0.07553	0.75	0.0000566	175.06
9	0.98	0.00234	0.03453	0.66	0.0000657	548.06
10	0.97	0.00244	0.04632	0.83	0.0000575	541.06
Average	0.98	0.004603	0.053176	0.776	7.28E-05	596.16

The result shows a comparison between the neural network prediction model and the linear regression prediction model. From the result, the regression performance, R is 0.98 as against 0.776 achieved with linear regression, thus giving a percentage improvement of 20.4%. For MSE, both the FFNN and the linear regression achieved a minimal error value which is acceptable. However, for the RMSE performance, the FFNN is 0.053176 which is very good as it is approximately zero, but with the linear regression, the value is extremely high at 596.16 which makes the linear regression prediction model not reliable. Table 3 shows the validation performance of the ETS model.

Table 3: Validation of the ETS model

S/N	ROC	MSE	Error (%)	Accuracy (%)
1	0.987	0.00251	1.30	96.7
2	0.977	0.00265	1.12	97.3
3	0.967	0.00564	1.47	95.9
4	0.981	0.00446	1.08	98.1
5	0.979	0.00767	1.30	96.7
6	0.974	0.00353	1.13	97.2
7	0.976	0.00734	1.13	97.2
8	0.989	0.00745	1.28	96.6
9	0.969	0.00234	1.31	96.8
10	0.978	0.00244	0.93	99.1
Average	0.9777	0.004603	1.205	97.16

The result shows that the average ROC is 0.9777 which is very good as it implies good classification performance. The MSE value is 0.004603Mu which is also good as it indicates tolerable training error. The loss percentage which is the percentage of false classification is averagely 1.205% and the accuracy is 97.16% which all implies correct classification performance.

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Integration of the ETS

The system integration of the ETS showed how the ETS model developed and evaluated was used to implement the EST for the detection of employment fraud. The result of the ETS when tested with fingerprint data of NYSC discharged corps member is as presented inFigure 15.

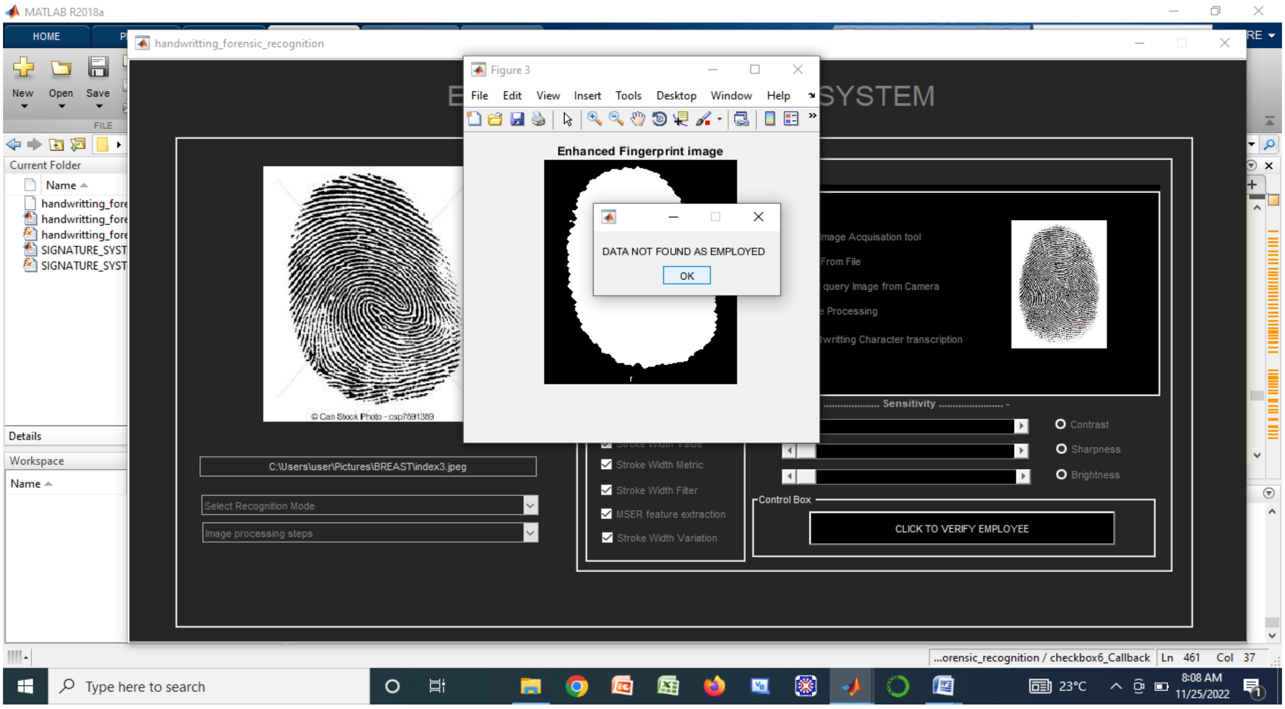

Figure 15: Result of ETS system

The software was able to detect that the fingerprint of the job applicant was not found in the database of the FMLEP. The implication of the result is that the person has not been employed by the government and hence can be considered for employment. Figure 16 shows the performance of the data process utilized to enhance the success of the ETS. The input fingerprint was denoised using the median filter approach to reduce noise for filtration and then enhancement to improve quality of extraction. The feature extraction approach used is the statistical method which extracts the interesting feature vectors of the image for classification and then the final recognition result. This is as shown in figure 17 which indicates an already existing employee of the FMLEP who applied for another government job position.

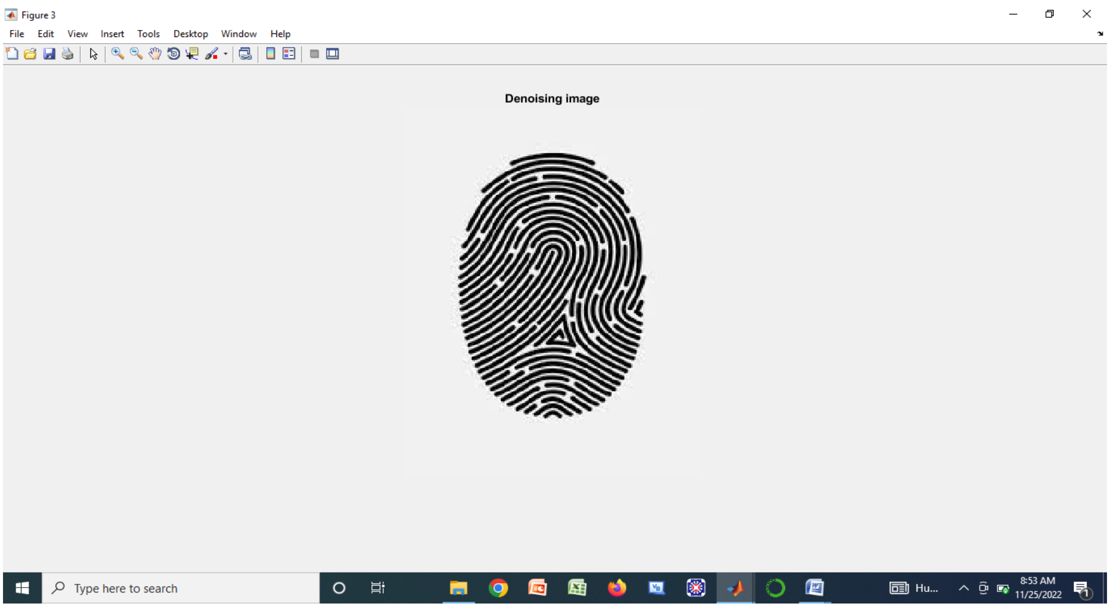

Figure 16. Data processing output with median filter

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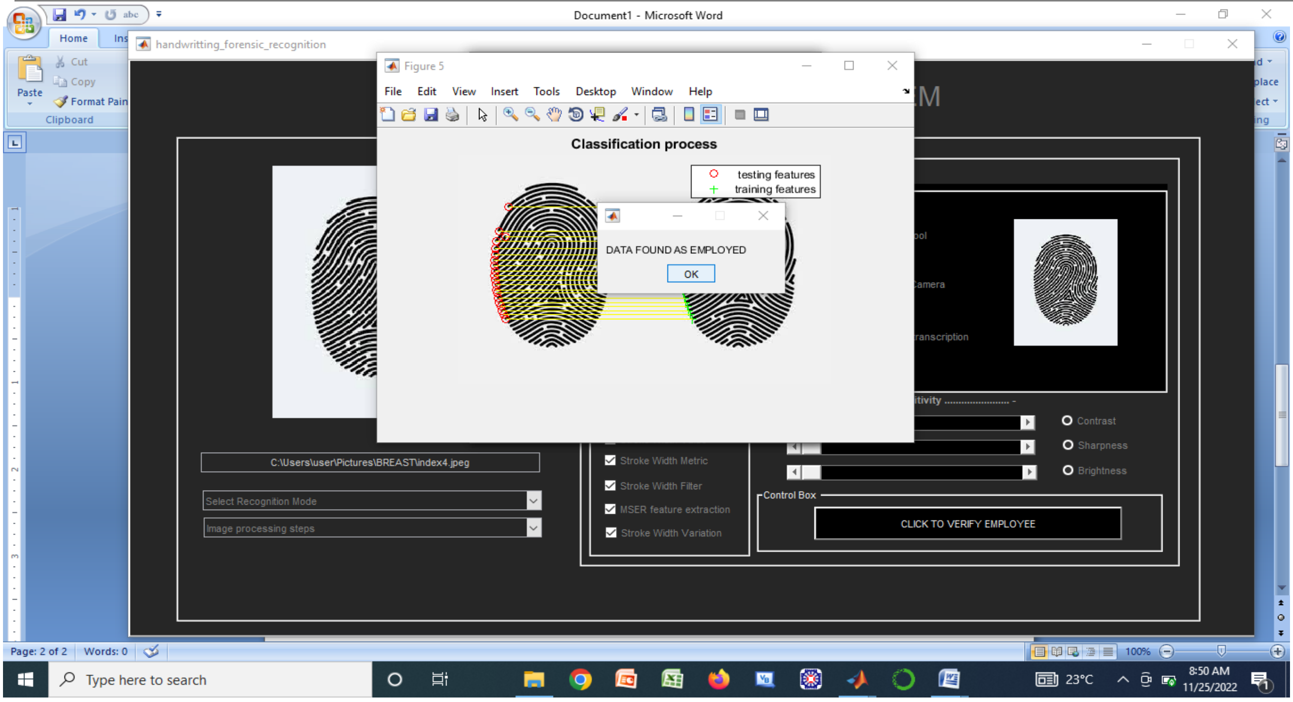

Figure 17. Result of ETS with an existing government staff

CONCLUSION

This research developed a DNS powered by machine learning techniques to address the persistent issue of unemployment in Nigeria. A comprehensive literature review revealed a significant gap in the application of intelligent systems to unemployment management. To bridge this gap, we implemented a digital twin model that integrates an ETS with predictive analytics. The ETS was designed to tackle issues such as multiple government employments and the prevalence of ghost workers by verifying employment status using biometric data. In addition, a machine learning-based prediction model was developed to estimate the number of unemployed graduates from HEIs expected to complete the NYSC program over the next ten years. This forecasting capability enables government agencies to make data-driven decisions for strategic job creation and workforce planning. The system was simulated and tested, with results showing that the feed-forward neural network outperformed the linear regression model by 20.4% in predictive accuracy. The model reliably forecasted unemployment trends and ensured that projected job opportunities could be matched with qualified graduates. This demonstrates the potential of the proposed DNS-based approach to significantly enhance employment planning and policy formulation in Nigeria.

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