Development of an Intelligent Fire Hazard Detection System Using Enhanced Machine Learning Technique

Odo F.E[1], Ituma C.[2], Asogwa T.C.[3], Ebere U.C.[4]
[1,2,3]*Enugu State University of Science and Technology*
[4]*Destinet Smart Technologies*

Abstract: **This work was targeted on the development of an intelligent fire hazard detection system using enhanced machine learning technique. The study reviewed many literatures which revealed the problems fire hazard has causes over the years, and also the efforts proposed to solve these problems, but despite the success achieved, there is still great room for improvements This was achieved using Dynamic Systems Development Model (DSDM) methodology which accommodates all necessary functionalities such as modeling diagram, mathematical models, algorithms and simulation based implementation. The model of the wavelet transform was developed and the decomposed output was feed to a Feed Forward Neural Network (FFNN) which was trained with fire data collected from the Nigerian Fire Service Department and back propagation algorithm, to achieve an intelligent fire hazard detection algorithm. The algorithm was implemented with Mathlab and then tested. The result showed a regression performance value of 0.96152, accuracy of 93.33% and MSE value of 0.000103Mu which all indicated system reliability.**

***Keywords*: Fire Hazard, Machine Learning, Wavelet Transform, Neural Network, Matlab**

I. INTRODUCTION

Fire hazard detection and prevention is vital for the safety of lives and properties in residential and public localities such as homes, hotels, industries, bar among other places. This topic has become very important due to the increase rate of fire accidents occurring both indoors and outdoors today. The outdoor involves mainly wild fire events which damages the ecosystem vegetation and wild lives with high economic impact which although can be recovered with time. However, the most devastating is the indoor fire hazards which often claim human lives and household properties. This is the most devastating as human lives is priceless and cannot be recovered when lost.Some of the cases of these indoor fire events are discussed in (Chen et al., 2017; Collins et al., 2019; Daniel et al., 2015).

According to (Collins et al., 2019), indoor fire hazard is caused mainly due to careless activities with fire during cooking (e.g reckless use of liquid petroleum gas (LPG) cylinder which can be very dangerous when carelessly exposed to flame). Other causes are poor electrical connections in structural designed which can short circuit and cause fire outbreaks, careless use of candle, smoking at home, faulty wiring among other reasons. In a report releases by the National Fire Protection Association (NFPA, 2019), it was revealed that 48% of all indoor fire hazard are causes by reckless cooking activities, with global death rate which ranges from 100 to 400 every year and hence the need for real time fire detection and prevention system. Fire detection and prevention system are devices specially designed to detect fire hazard before they escalade and notify the user for immediate control measures.

According to Uche (2021), the methods of fire hazard detection are video based method, image processing based, artificial intelligent based and sensor based methods respectively. These methods despite their success all have their disadvantages, like the sensor based which suffers issues of false alarm, artificial intelligence based technique which suffers issues of unreliability due to unavailability of standard training data for fire detection research, the image processing based technique which is limited due to poor fire detection accuracy and the video based which is limited due to the high cost of sophisticated camera to collect quality fire frames for processing. Nevertheless, it was observed that the artificial intelligence based approach provides the best efficiency when compared to the other counterparts. Artificial intelligence (A.I) system has the ability to also improve other methods to achieve optimal fire detection result in real time. According to Sharma (2020) A.I are intelligent system which has ability to learn and make decisions based on data collected from the environment or set of rules.

A.I is of four categories which are expert system, fuzzy logic, genetic algorithms and machine learning. Among the categories of A.I, the use of machine learning (ML) have over shadowed other A.I techniques due to its success in various field of applications and also due to its ability of make decisions based on the patterns extracted from the real time problem, when compared to the other A.I techniques which are rule based dependent for decision making (Wolfgang and Hochschule, 2017). According to (Ituma and Asogwa, 2018), ML is set of algorithm which has ability to learn from training dataset and accurately solve classification and regression problems. The ML algorithms ranges from support vector machine (SVM), Artificial Neural Network (ANN), K nearest neighbor (K-NN), Navive Bayes, among others and are classified under supervised, unsupervised, semi supervised and reinforcement learning respectively (Jang et al., 2017; Punam and Shmik, 2012).

In solving problem of fire hazard detection and prediction system which is an unsupervised learning problem, the use of ANN have emerged as the most reliable in recent times, when compared to the other ML algorithms. The ANN is set of biological neurons which have weights, bias and activation function, with the ability to learn patterns and make accurate decisions (Nikos et al., 2019). ANN are of many types such as the feed forward neural network, convolutional neural network, recurrent neural network, multi layered neural network among others as discussed in (Kaabi et al, 2018; Muhammad et al., 2018; Alex et al., 2012), but the use of feed forward neural network provides the best result in solve time series problem like the case study, but has been limited due to the poor quality of training data available. To address this, the researcher proposes an intelligent fire hazard detection and prediction system using improved machine learning technique. The technique will be improved using wavelet transform to optimize the reliability of the input data before feeding forward to the neurons for system identification and training. This when achieved will improve the efficiency of the ANN performance and provide quality and reliable fire hazard detection and prediction system.

II. LITERATURE REVIEW

Olivares-Mercado et al. (2018) proposed a method of early fire detection and prediction by analyzing visual smoke characteristics such as color, dynamic texture, gray tones, etc. The system was tested using standard videos containing smoke. However despite the success, false alarm rate was high due to the lack of adaptive learning intelligence on the approach used. This color based approaches can be improved using artificial intelligence techniques.

Hu et al. (2018) used long short term memory (LSTM) for fire detection, where the CNN features are extracted from optical flows of consecutive frames, and temporally accumulated in an LSTM network. The final decision is made based on the fusion of successive temporal features. Their approach despite the success however, the data collection technique used in this research lacks computer vision intelligence and hence feed the Deep learning with poor quality data for training.

Muhammad et al. (2018) proposed a fire surveillance system based on a fine-tuned CNN fire predictor. This architecture is an efficient CNN architecture for fire detection, localization, and semantic understanding of the scene of the fire inspired by the Squeeze Net architecture. The problem with the system despite the high success rate is the poor and limited dataset for fire research work. Although the CNN-based approaches provide excellent performance, it is hard to capture the dynamic behavior of fire and the unavailability of a complete fire dataset limited the applications.

Blagojevice et al. (2019) presented a novel approach for fire detection in a working and living environment. The paper suggested a new approximation function for fire flame edge detection in early stage of fire development. The function was used to predict temperature behavior as it rises proportionally due to fire growth at a specific time interval. However, despite the success of the approach, the system suffers from delay time, which is vital for effective fire detection process.

Olivares-Mercado (2018) proposed a method of early fire detection by analyzing visual smoke characteristics such as color, dynamic texture, gray tones, etc. The system was tested using standard videos containing smoke. However, despite the success, false alarm rate was high due to the lack of adaptive learning intelligence on the approach used. This color based approaches can be improved using artificial intelligence techniques.

III. METHODS

The methods used for the development of the proposed system are data collection, data acquisition, data processing, wavelet transform, artificial neural network, training, prediction and detection. This was achieved using Dynamic Systems Development Model (DSDM) methodology which accommodates all necessary functionalities such as modeling diagram, mathematical models, algorithms and simulation based implementation solution.

Data collection

For the development of the proposed system, data collection was done from the Nigerian Fire Service department (Enugu State Branch) as the primary source of data collection. This was achieved using an authorized letter from the institution, signed by the project supervisor, which request the dataset for the purpose of this research only (See letter in Appendix A). The data sample size contains 3800 features of fire data collected from various fire hazard events recorded over the last five years. The data was collected in image formatted and then used database toolbox in Matlab to convert to Matlab files. The secondary source of data collected was Github repository which provided important fire data features omitted from the primary dataset which is the 300 sample size of candle fire data. This data was integrated also collected in its image format and then used the Matlab database toolbox to convert to Matlab files and also stored with the original data collected. The overall sample size of data collected is 4100 and was converted into m.files and stored as the training dataset. The fire data samples are presented in figure 1;

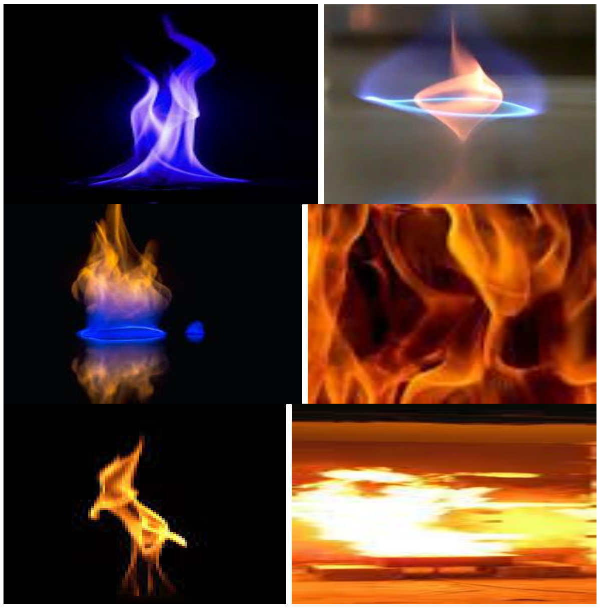

Figure 1: Fire samples

***Data acquisition*:** This is the process of capturing fire data by the image acquisition device (camera sensor) and then feed to the proposed artificial intelligent system for training, prediction and fire detection in real time.

Data processing: Fire is a dynamic system when it burns and the data collected are associated with various noises. This process ensured that the fire data is processed using wavelet transform filter which was designed in the next chapter to extract quality fire data in both frequency and time domain.

Wavelet transform: Wavelet transform is perceived as a very promising technique for this type of applications because it has the capacity to simultaneously localize signal in both frequency and time domain (Majid et al., 2013). It may be used to distinguish fire data waves from serious noise drifts. Wavelet transformation represents the temporal features of signal at different resolution providing better analysis of real ire signals, which is characterized by cyclic occurring patterns at difference RGB wavelets. This was use in this research to improve the quality of data feed to the artificial neural network model for training.

Artificial Neural Network (ANN): ANN is a biological inspired neuron which has weight, bias and activation function with the ability to learn patterns from training dataset and make accurate decisions (Majid et al., 2009). According to Sharma (2020) the ANN are among the most employed machine learning algorithm which are most efficient in solving pattern recognition problems. They are used in this study to develop the prediction and detection model for fire hazard.

Training: This is the process of learning the ANN with the fire hazard patterns using a training algorithm. The training algorithm used in this research is the back propagation type which uses feedback approach to feed each layer of the neurons the output of each step training response until the fire patterns are correctly learned.

Detection: This is the process where the neural network collected data of fire, train then to detect its time series behavior as hazard or not hazard. The result of the prediction is the fire detection process which was used to trigger control measures like the alarm and email notification.

IV. SYSTEM DESIGN

The model was developed using wavelet transform as a signal processing tool and then feed to processed output fire data as a nonlinear auto regressive model of neural network architecture for training and development of the predictive model. The wavelet model is presented below;

Modeling of the wavelet transform filter

Wavelet transform was used here as a data processing tool which analyzed the fire captured in frequency and time domain. The type of wavelet transform used here is the Discrete Wavelet Transform (DWT) type. In the DWT, the signal is decomposed into two levels such as coarse approximation and detail information. DWT have two sets of functions. Scaling functions are performed by low pass filter and wavelet functions are performed by high pass filter. A signal in time domain is decomposed into different frequency bands by passing it into successive high pass and low pass filters. The original signal is passed through a half band high pass filter which is followed by low pass filter, with the output down sampled. This output is a constituent of various levels of wavelet decompositions and the process report until a depth transformation of the data is achieved and then feed for training. The wavelet algorithm is presented below;

PSEUDO CODE OF Wavelet Transform (ALGORITHM 1)

The following steps are used to provide to apply wavelet transform:

Start

Load data captured from camera
Dimension into 300 x 240 pixels values
Activate scaling and wavelet function

Decompose into time domain with high and low frequency bands

Get the depth transform of the data

Return

End

Model of Machine learning algorithm

The machine learning algorithm is developed using Artificial Neural Network (ANN). The type of ANN model used here is the Feed Forward Neural Network (FFNN). The FFNN an interconnected massive parallel computational models, units or nodes, whose functionality mimic the animal neural network in order to process information from the input to the output using the connection strength (weight) obtained by adaptation or learning from a set of training patterns. The modelling description of the neural network process is shown in equation 1 below. In the figure the neuron is a unit of computation that reads the inputs given, processes the input via its weights, sum the result collected and transform into statistical values using the activation function and gives the output in processed form. The weighted sum of the inputs neurons are presented as;

$$v_k = \sum_{i=1}^{N} w_{ki} x_i \qquad (1)$$

Where

x_i is the neuron's input from the CCTV fire camera. w_{ki} is the corresponding weight to the input x_i.

The neuron's output is obtained by sending the weighted sum v_k as the activation function φinput that resolves the output of the specific neuron. $y_k = \varphi(v_k)$. A step function with threshold t can be used to express a simple activation as, however, bias is most time used instead of a threshold in the network to learn optimal threshold by itself by adding $x_o = 1$ to every neuron in the network. These neurons are interconnected to form hidden layers in a feed forward manner as shown in the modelling DFD in figure 2;

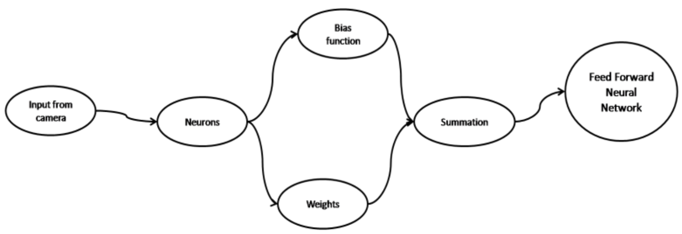

Figure 2: DFD of the FFNN model

The model in equation 1 presented a single neuron interconnected to form the model of the FFNN in figure 2; these models are summed and then activated as shown in the model of equation 2 using nonlinear activation function.

$$a_1^n = f(w_{11}^n x_1 + w_{12}^1 x_2 + w_{13}^1 x_4 + b_1^1) \quad (2)$$

The model in equation 2 presented the neural network architecture with as weights, b as bias, x is time series, a as the activation function, n number of interconnected layers in a feed forward configuration which was trained. The modeling diagram of the activated FFNN is presented in figure 3 using the DFD;

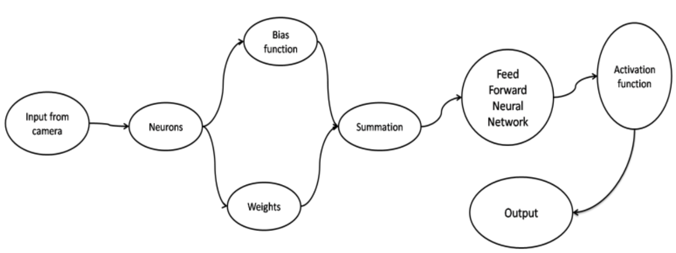

Figure 3: The activated FFNN model

The model in figure 3 presented the FFNN activated to form statistical values between 1 and 0 for training using back propagation algorithm. The neural network configuration was done using the data in the table 1. The training algorithm is presented in figure 4;

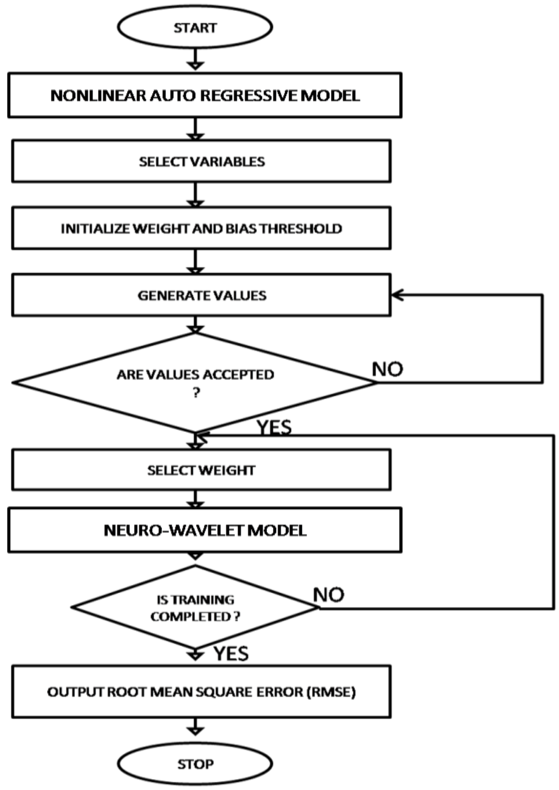

Figure 4: The back-propagation algorithm

Table1: Neural Network Parameters

Parameters	**Values**
Train epoch values	16
The network hidden layers	10
Max epoch values	30
No. delayed reference input	1
Maximum feature output	3.1
Number of non hidden layers	2
Maximum interval per sec	2
No. delayed output	1
No. delayed feature output	4
Minimum reference value	-0.7
Maximum reference value	0.7

Model of the Enhanced Machine learning algorithm

The enhanced machine learning algorithm was developed the wavelet transformation function in algorithm 1. The pseudo code of the enhanced machine learning algorithm is presented below;

PSEUDO CODE (ALGORITHM 2)

1. *Start*
2. *Start camera*
3. *Collect fire data*
4. *Activate wavelet function for transformation using algorithm (1)*
5. *Feed forward the decomposed fire data into the FFNN in equation 2*
6. *Train with back propagation algorithm in figure 4*
7. *Check training until desired epoch is achieved*
8. *If = true*
9. *End training*
10. *Return*
11. *Else*
12. *Retrain until desired epoch is achieved*
13. *Record reference fire model for time series fire detection*
14. *Use reference model for fire detection*
15. *End*

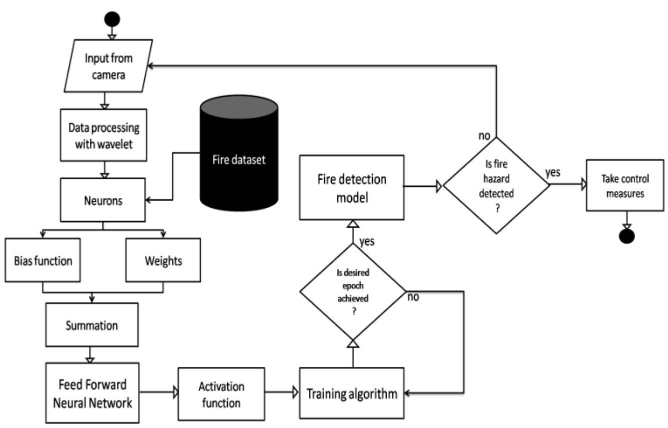

Figure 5: Activity model of the enhanced machine learning algorithm

The model in figure 5 shows the logical data flow from the camera as fire data are collected and processed using discrete wavelet transform which transform the data into frequency and time domain using scaling and wavelet functions to for multiple decompositions of wavelet features which were feed to a neural network for training using back propagation algorithm to form a reference fire detection model, employed for time series detection of fire hazard.

V. IMPLEMENTATION

The system developed was implemented using neural network application software in simulink. This was achieved using the models developed which was used to build a neural network toolbox, image processing toolbox, data base toolbox, wavelet transform toolbox, signal processing toolbox, statistics and machine learning toolbox to achieve the new system.

VI. RESULTS AND DISCUSSIONS

This section presented the result of the wavelet processing output, showing how the fire data was transformed and filter out noise. Then the performance of the training process was examined and validated.

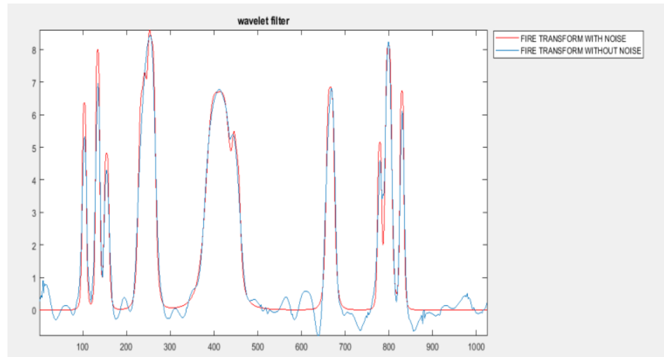

Figure 6: The wavelet filter

The figure 6, presented the performance of the wavelet filter used to process the data collected and provide a reliable data as shown in the figure 7;

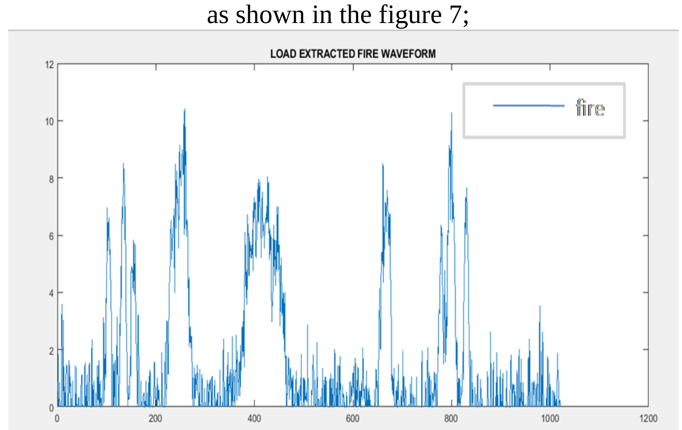

Figure 7: The filtered fire signal

VII. RESULT OF THE FFNN TRAINING

The performance of the FFNN training was evaluated using regression analyzer, Mean Square Error (MSE) analyzer and Confusion matrix analyzer. The results were measured from the neural network training App. The Regression (R) analyzer was used to measure the system reliability and acceptability. The aim of this regression is to achieve R value =1. The performance of the regression is presented in figure 8;

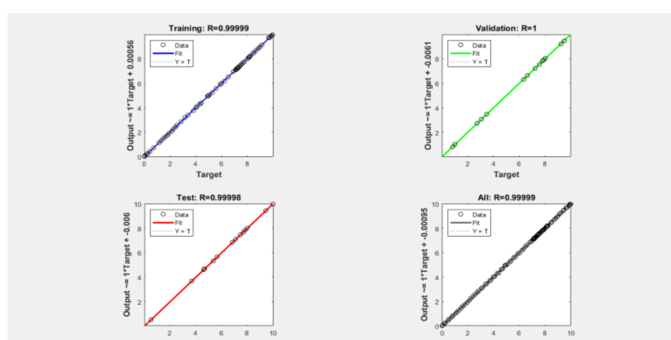

Figure 8: The Regression performance

From the result presented in figure 8, it was observed that the regression performance of the intelligent fire detection system developed is R= 0.999. The implication of the result showed that the fire detection system is very reliable and also the fitting of the data in each subset shows that during the training process, no overshoot or under shoot occurred, implying that the neural network correctly learns the fire data and detects hazards accurately. The accuracy of detection is evaluated in the confusion matrix of figure 9;

Figure 9: Confusion matrix of the system

The result in the figure 9 presented the confusion matrix of the intelligent fire hazard detection system. The aim of this analyzer is to measure the accuracy of the system performance and also justify the performance of the regression analyzer already discussed. The result confusion matrix was measured using the average of the test, train and validation sets and the result showed that the 96.7% accuracy was achieved for correct detection of fire hazard with 3.3% wrong classification. The implication of this result showed that the use of the wavelet which made the data feed to the FNN for training was very affective as the system developed is very accurate and reliable.

The next result presented the MSE performance. The focus of this tool is to measure the error value of the training process. This tool is like an opposite of the regression as the criteria for measurement is to achieve MSE value of zero (MSE=0) or approximately. The result in the figure 10 presented the MSE performance.

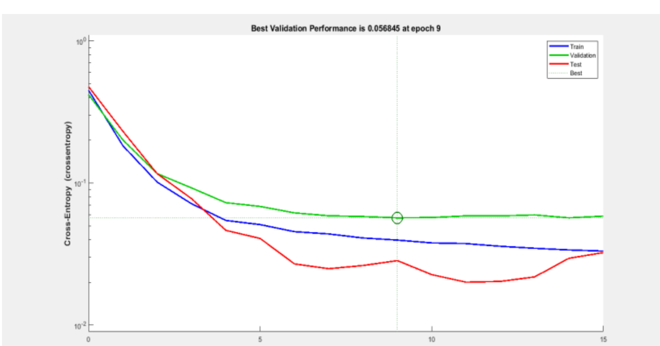

Figure 10: MSE performance

The figure 10 presented the MSE performance of the intelligent fire hazard detection system. From the result it was first observed that the multi set patterns correlated in the same direction which shows a good performance of the neural network tool. Secondly it was observed that the MSE value is 0.056846Mu at epoch 9. The implication of this result showed that at this epoch value, the FFNN tool have perfectly learned the fire feature vectors and then achieved the necessary reference fire detection model for time series classification.

System Validation

To validate the system developed using the result achieved, tenfold validation technique was used which iteratively performance the training, testing and validation process in tenfold. The results are presented as shown in table 2;

Table 2: Result of the validation process

S/N	Accuracy (%)	MSE (Mu)	Regression
1	96.07	0.000103	0.99043
2	94.88	0.000100	0.99622
3	94.43	0.000121	0.97712
4	96.13	0.000130	0.99062
5	94.83	0.000141	0.96059
6	92.12	0.000103	0.96042
7	91.95	0.000103	0.95804
8	91.12	0.000093	0.97077
9	90.21	0.000109	0.97016
10	91.83	0.000098	0.95079
Average	93.33	0.000103	0.96152

The result in table 2 presented the validation performance of the system using tenfold technique. The result achieved an average accuracy of 93.33%, MSE value of 0.000103Mu and regression of 0.96152.

VII. CONTRIBUTION TO KNOWLEDGE

i. An enhanced machine learning based fire hazard detection system was developed
ii. Wavelet transformed was used to improve the reliability of FFNN

VIII. CONCLUSION

This research has successfully developed and presented an intelligent fire hazard detection system which is reliable and accurate. This was done using signal processing tool designed with wavelet transform which has the ability to process simultaneously fire data in frequency and time domain. This processed wavelet decomposition of fire was then feed to an already trained FFNN algorithm for detection and classification of fire hazard in indoor environments. The result when tested showed that the new system is very reliable with a regression performance value of 0.96152 and MSE value of 0.000103Mu.

REFERENCE

[1] Alex Krizhevsky, Geoffrey Hinton, and Ilya Sutskever (2012) " ImageNet Classification with Deep Convolutional Neural Networks". 2012 Image Large Scale Visual Recognition Challenge.

[2] Blagojevic M, Petkovic M. (2019), "Predicting Fire In Early Stage-A New Approach, Working and Living Environmental Protection" ; IJER,Vol.2, No.1, pp.19-26.

[3] Chen, T.H.; Wu, P.H.; Chiou, Y.C (2017). An early fire-detection method based on image processing. In Proceedings of the International Conference on Image Processing (ICIP), Singapore, 24–27 October 2017; pp. 1707–1710.

[4] Collins A., Lipton, T. Kanade, H. Fujiyosh, D. Duggins, Y. Tsi, D. Tolliver, N. Enomoto, O. Hasegawa, P. Burt, and L. Wixson (2019). A system for video surveillance and monitoring. In Proc. Of the American Nuclear Society (ANS) Eighth International Topical Meeting on Robotics and Remote Systems, 2019

[5] Daniel Y. T. Chino, Letricia P. S. Avalhais, Jose F. Rodrigues Jr., Agma J. M. Traina (2015) "BoWFire: Detection of Fire in Still Images by Integrating Pixel Color and Texture Analysis", Proceedings of the 28th SIBGRAPI Conference on Graphics, Patterns and Images, 2015.

[6] Hu C. Tang P. Jin W. He Z. Li W. (2018) "Real-Time Fire Prediction Based on Deep Convolutional Long-Recurrent Networks and Optical Flow Method". In Proceedings of the 37th Chinese Control Conference (CCC), Wuhan, China, 25–27; pp. 9061–9066.

[7] Ituma C. and Asogwa T.C. "The Application Of Machine Learning For Digital Recognition Of Identical Twins To Support Global Crime Investigation" International Journal of Computer Science and Engineering (IJCSE), Issues 12; 2018,Vol 4 pp. 427–433

[8] Jang, J.Y.; Lee, K.W.; Kim, Y.J.; Kim,W.T. S-FDS (2017): A Smart Fire Detection System based on the Integration of Fuzzy Logic ; J. Inst. Electron. Inf. Eng. 2017, 54, 50–58.

[9] Kaabi, R.; Sayadi, M.; Bouchouicha, M.; Fnaiech, F. (2018); Moreau, E.; Ginoux, J.M. Early smoke detection of forest wildfire video using deep belief network. In Proceedings of the 4th International Conference on Advanced Technologies for Signal and Image Processing (ATSIP), Sousse, Tunisia, 21–24 March 2018; pp. 1–6.

[10] Muhammad, K.; Ahmad, J.; Lv, Z.; Bellavista, P.; Yang, P.; Baik, S.W. (2018); Efficient Deep CNN-Based Fire Detection and Localization in Video Surveillance Applications. IEEE Trans. Syst. Man Cybern. Syst. 2018, 99, 1–16.

[11] Majid B., Nirvana M., Paul H., (2009) "Use of AI Techniques for Residential Fire Detection in Wireless Sensor Networks. Conference: Proceedings of the Workshops of the 5th IFIP Conference on Artificial Intelligence Applications & Innovations (AIAI-2009), Thessaloniki, Greece

[12] Majid J., Jamia M., Abdul Q., Jamia M., Rizwan M., (2013) "Wavelet-FFNN Based fault Location Estimation of a Transmission Line" Electrical Engineering Research 1(3):77-82

[13] Nikos Aspragathos, Eleftherios Dogkas, Pavlos Konstantinidis, Panagiotis Koutmos, Nefeli Lamprinou, Vassilis C. Moulianitis, Georgios Paterakis, Emmanouil Z. Psarakis, Evangelos Sartinas, Konstantinos Souflas, Georgios Thanellas, Georgios Tsiourlis, Nikitas Xanthopoulos and Panteleimon Xofis (2019). From Pillars to AI Technology-Based Forest Fire Protection Systems, Intelligent System and Computing, Yang (Cindy) Yi, IntechOpen, DOI: 10.5772/intechopen.86904.

[14] Olivares-Mercado J., Toscano-Medina K., Sánchez-Perez G., Hernandez-Suarez A., Perez-Meana H., Sandoval Orozco A.L., García Villalba L.J (2018). Early Fire Detection on Video Using LBP and Spread Ascending of Smoke; Comput. Sci. Inf. Syst. 2018;12:63–89.

[15] Punam Patel, Shamik Tiwari (2012) "Flame Detection Using Image Processing Techniques", International Journal of Computer Applications (0975 – 8887) Volume 58–No.18, November 2012.

[16] Sharma, V. (2020). Deep Learning: Introduction to Recursive Neural Network (Assessed 12 September 2021)

[17] Uche Anawenze (2021) "Development of fire hazard detection system using computer vision based artificial intelligence technique" PHD disertation.

[18] Wolfgang E. and Hochschule R.W. (2017). Introduction to Artificial Intelligence, 2nd edition: Springer International Publishing AG Germany