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Classification of seismic signal based on DWT and Artificial Neural Network

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ABSTRACT

Event detection using seismic signals is a very important problem. Several techniques have been developed, but it is difficult to achieve acceptable event capture performance in outdoor environments. In this article, we propose a ground motion detection technique that uses the energy of seismic signals detected in different spectral ranges, which is classify the signal based on Multi-layer Perceptron (MLP)MLP. A discrete wavelet transform is used to analyse seismic signals, extract certain features, and classify the data using a Multi-layer Perceptron (MLP) neural network. The suggested system is capable of detecting two different signal kinds. The proposed method trained and tested neural network base classifier using Darfiled earthquake from Newzealand ground motion database. The simulation findings demonstrate that, when applied to 100 signals, comprising signals from major and minor earthquakes. Based on the results, MLP can effectively classify signals based on their features. The results obtained from the simulation has been inferred that the accuracy of classification of the proposed algorithm is 98%. As a result, DWT is used Seismological event analysis can be improved by using MLP neural network techniques.

Keywords: Seismic signal, classification, multilayer perceptron neural network, feature extraction, Pattern Recognition, Classification.

1. INTRODUCTION

The identification of earthquake events is one of the tasks of earthquake rapid report. The identification accuracy is of great significance for improving the quality of earthquake catalogue and seismological research. In the field of science and technology, wavelet analysis has gained a prestigious position in wide areas, including seismic signal processing and analysis. On September 4, 2010, at 4:35 am, a 7.1-magnitude earthquake shook the Canterbury region of New Zealand. On the previously unknown Greendale fault, 11 kilometres under the little rural village of Darfield, it was centred. There were about 370,000 people living in Christchurch City, which is located 40 kilometres east of Darfield, at the time of the earthquake. In seismic signal processing, seismic signal parameters are noise, location, and epic centres, arrival times, can be analysed effectively. Artificial neural networks have gained more attention recently for handling a variety of real-world issues where traditional methodologies are either unavailable or deemed insufficient to adequately explain and analyse the problem's behaviour. The strength of neural networks rests in their capacity to readily learn the input/output connection from the data being modelled and in their ability to model exceedingly complicated non-linear mappings. Contrarily, the most conventional approaches demand a thorough comprehension of the issue. In this study, two classes are taken into account. Which are: Minor earthquake (Min) and major earthquake (Max).

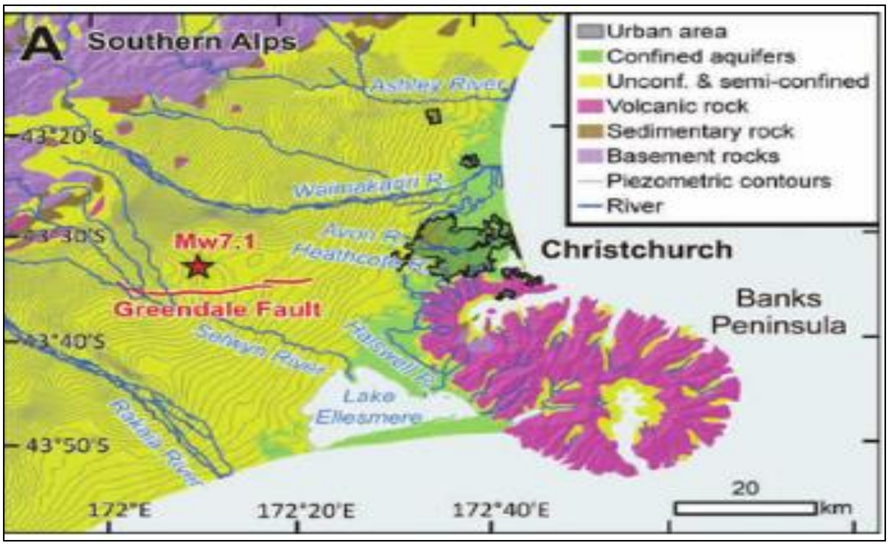

Figure 1 Geographical Representation of Darfield earthquake, Newzealand

1.1 Machine Learning Methodology

A computer programme is said to learn from experience E with regard to a class of tasks T and a performance measure P if its performance at tasks in T, as measured by P, increases with experience E, according to employed an artificial neural network for this study (ANN)[1]. The well-known Multilayer Perceptron (MLP) artificial neural network has at least three layers: input, hidden, and output. The neurons used in such a network employ activation functions, whose outputs are linked to neurons in the layer below to create a nonlinear mapping. The difficulty of determining the quantity of neurons and hidden layers is another significant MLP-related factor. There are different types of ANN architectures, including feed forward networks, recurrent networks, and convolution networks. Feed forward networks are the most basic and consist of a series of layers where the output of one layer is fed as input to the next. The MLP has to be trained on a pair input/output set of data in order to learn to associate the inputs with the matching outputs before it can be used. Each sample from the training set is presented to the neural network during training, and a learning algorithm alters the network's weights to reduce the difference between the desired and observed outputs. Utilised.

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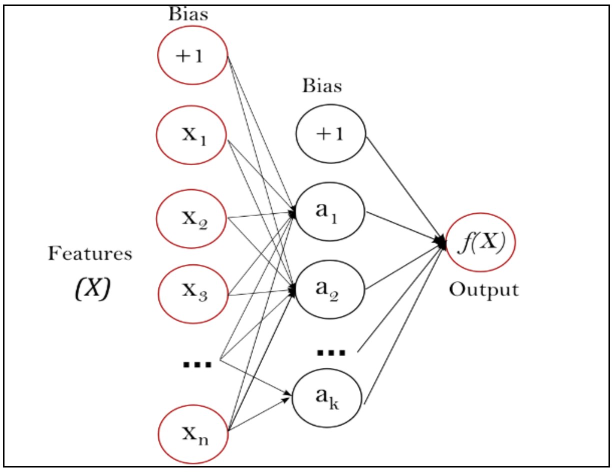

Figure 2 Multilayer Perceptron Neural Network

2. PROPOSED METHODOLOGY

The non-stationary signals are analyzed by using wavelet transform, which can be able to resolve features at various scales. The wavelet transform was presented at the beginning of the 1980s by Morlet, who used it to evaluate seismic data. The most popular neural network is the Multi-Layer Perceptron (MLP). Due to the fact that it needs a desired output in order to train, this kind of neural network is referred to as a supervised network. The MLP should be possible to develop a complete automatic seismic analysis system. The feature extraction stage and the classification step are the two basic processes that make up the issue. In the former, on the basis of the DWT, pertinent discriminant characteristics are retrieved from the seismic signal [2].

2.1 Discrete Wavelet Transform

The Discrete Wavelet Transform is a square integral of linear function. Multiscale transforms are used for non-stationary signals. Starting from a signal s of length N, two sets of coefficients are computed: approximation coefficients CA_1, and detail coefficients CD_1. These vectors are obtained by convolving s with the low-pass filter Lo_D for approximation and with the high-pass filter Hi_D for detail, followed by dyadic decimation. The length of each filter is equal to $2L$. For signal of length N, the signals F and G are of length $N + 2L - 1$, and then the coefficients CA_1 and CD_1 are of length [3].

$$\left[\frac{N-1}{2} + L\right] \qquad (1)$$

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\left(\frac{t-b}{a}\right) \ a, b \in R \ , a \neq 0 \qquad (2)$$

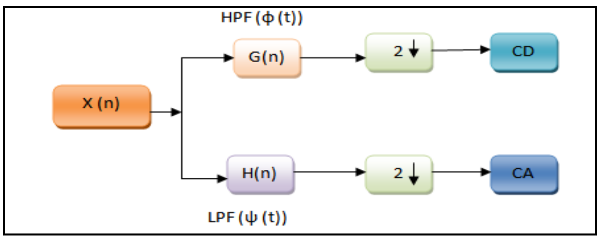

Figure 3 Decomposition of Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) is the digitization of the wavelet transform. In the Discrete Wavelet Transform (DWT), the values of *a* and *b* are restricted to discrete values on the time-frequency plane. The discrete wavelet bases are generated as $\left\{\Psi_{(m,n)}, m \in Z, n \in Z\right\}$ .There are several possible ways of discretizing the transforms (especially in the wavelet case), ·and which method to choose depends on the application.

$$\Psi_{(m,n)}(\mathrm{t}) = \frac{1}{\sqrt{|a_0|^m}}\left(\frac{x - nb_0|a_0|^m}{a}\right) \quad a, b \in R\,, a \neq 0 \tag{3}$$

$$a = a_0{}^m \tag{4}$$

$$T_{f\,(m,n)} = < f, \Psi_{(m,n)} > = \int_{-\infty}^{\infty} f(x)\, \Psi_{(m,n)}{}^{*}(x)\, dx \tag{5}$$

One concern about the DWT is how to build a complete discretized wavelet basis that could represent any signal fin the Hilbert space sufficiently, and to reconstruct the fin a numerically stable way from the T f{m.,n). Any function to be used as the kernel wavelet needs to meet the following admissibility conditions Ψ(t) should be absolutel y integrable and square in tegrable (i.e., its energy is finite)[4].

$$\int \Psi(t) < \infty \tag{6}$$

$$\int |\Psi(t)|^2\, dt < \infty \tag{7}$$

1. $\Psi(\omega)$ is band limited and has zero mean,

$$\int \frac{\Psi(\omega)}{\omega}\, d\omega < \infty \tag{8}$$

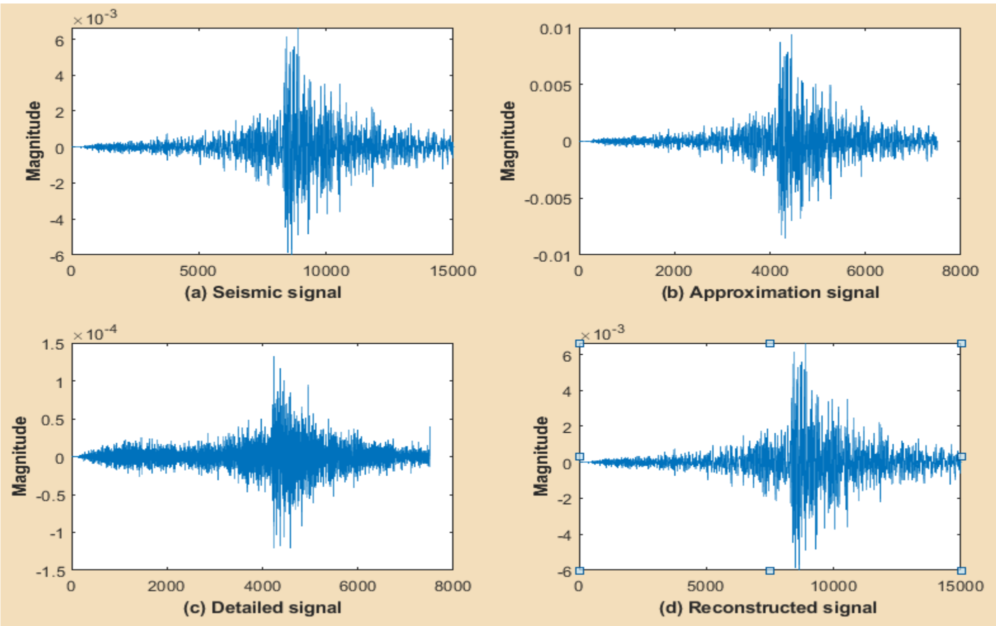

Figure 4 Decomposition of seismic signal by using DWT

The above figure 1 clearly show that function of the DWT. Then the seismic signal is decomposed into approximation coefficients (CA) and detailed coefficients (CD) in 7 levels as shown in figure 1 (b), (c). Figure 1(d) shows reconstructing signals are obtained by CA and CD coefficients.

2.2 Energy Distribution

In energy distribution which provides energy sub bands in each level. These sub bands were also used as features from seismic signal. This features can be evaluated by using artificial neural network.

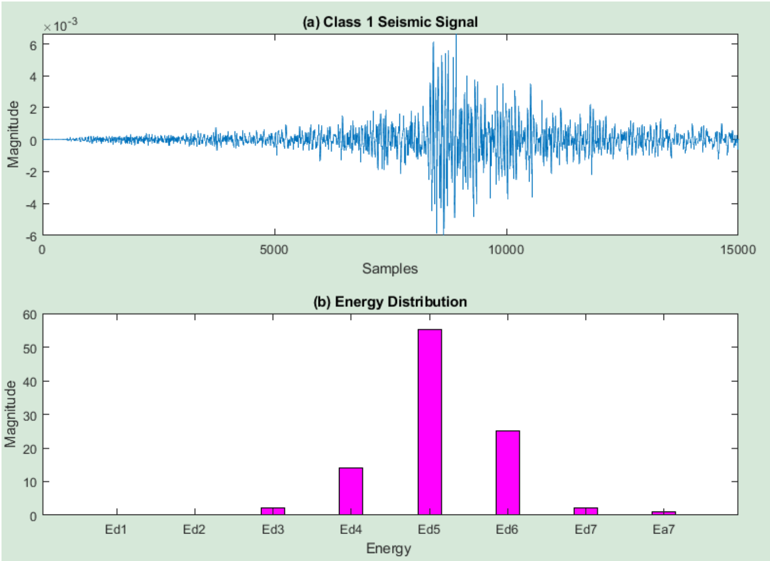

Figure 5 Energy Distribution of Class 1 seismic signals

In Figure 2 shows the information of seismic signal at energy scales, energy values determined the class of the seismic signal. The energy suddenly increases in the 5th energy sub band that includes the major signal [5].

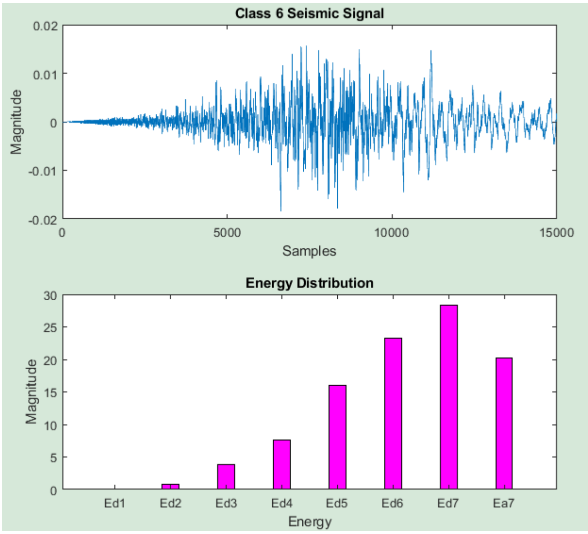

Figure 6 Energy Distribution of Class 2 seismic signals

As shown in figure 3 it is depicted that, that amount of energy present in each sub bands varies, then the energy has an abrupt change in the 7th energy sub band that includes class 6 signal of minor signal

2.3 Neural Network

Pattern recognition networks are feed forward networks that can be trained to classify inputs according to target classes [6]. The target data for pattern recognition networks should consist of vectors of all zero values except for a 1 in element i, where i is the class they are to represent. Neural networks rely on training data to learn and improve their accuracy over time. However, once these learning algorithms are fine-tuned for accuracy, they are powerful tools in computer science and artificial intelligence, allowing us to classify and cluster data at a high velocity[7].

In several domains, including signal processing and data compression, SVD has been utilised extensively for feature extraction from matrices. Singular values of the primary wavelet coefficient matrix can effectively capture the characteristics of seismic occurrences since they are intrinsic properties of a matrix and have strong stability [8].

One of the most well-liked supervised learning algorithms, Support Vector Machine, or SVM, is used to solve Classification and Regression issues. Nevertheless, it is largely employed in Machine Learning Classification issues. The SVM algorithm's objective is to establish the optimal line or decision boundary that can divide n-dimensional space into classes, allowing us to quickly classify fresh data points in the future. A hyperplane is the name given to this optimal decision boundary [9].

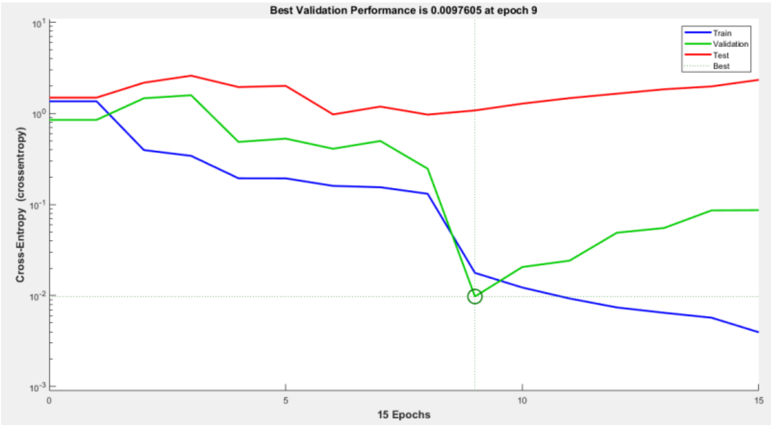

Figure 10 Performance state of neural network

The MLP neural network exhibits reasonable performance, and achieved that by enhancing the diversity and quantity of input characteristics, this system might function more precisely [10].

2.4 Performance Measures

2.4.1 Accuracy

The overall **accuracy** of a model is simply the number of correct predictions divided by the total number of predictions. An accuracy score will give a value between 0 and 1, a value of 1 would indicate a perfect model.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \times 100 \tag{9}$$

2.4.2 Specificity

Specificity is calculated as the ratio of true negatives (TN) divided by the total number of tries to classify anything as negative (TP + FP), where FP represents the number of times a classification should have been negative but was incorrectly declared as positive. In conclusion, Specificity functions as an index of unclassified negative categories.

$$\text{Sensitivity} = \frac{TN}{TP+FP} \times 100 \tag{10}$$

2.4.3 Precision

Precision measures how good the model is at correctly identifying the positive class.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{11}$$

2.4.4 Recall

Recall shows how good the model is at correctly predicting **all** the positive observations in the dataset.

$$\text{Recall} = \frac{TP}{TP+FN} \tag{12}$$

2.4.5 F1 score

The **F1 score** is the harmonic mean of precision and recall. The F1 score will give a number between 0 and 1. If the F1 score is 1.0 this indicates perfect precision and recall. If the F1 score is 0 this means that either the precision or the recall is 0.

$$\text{F1}=\frac{TP}{TP+\frac{1}{2}(FN+FN)} \tag{13}$$

2.4.6 Kappa

The **kappa** statistic compares the observed accuracy to an expected accuracy or the accuracy expected from random chance. One of the flaws of pure accuracy is that if a class is imbalanced then making predictions at random could give a high accuracy score. Kappa accounts for this by comparing the model accuracy to the expected accuracy based on the number of instances in each class.

$$\text{Kappa}=\frac{Observed\ Accuracy-Expected\ Accuracy}{1-Expected\ Accuracy} \tag{14}$$

Essentially it tells us how the model is performing compared to a model that classifies observations at random according to the frequency of each class.

2.4.7 MCC

MCC (Matthews Correlation Coefficient) is generally considered one of the best measurements of performance for a classification model. This is largely because, unlike any of the previously mentioned metrics, it takes all possible prediction outcomes into account. If there are imbalances in the classes this will therefore be accounted for.

$$\text{MCC}=\frac{TP\times TN-FP\times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{15}$$

The MCC is essentially a correlation coefficient between the observed and predicted classifications. As with any correlation coefficient, its value will lie between -1.0 and +1.0. A value of +1 would indicate a perfect model.

RESULTS AND DISCUSSION

The extensive range of tests carried out to examine the inherent potential of MLP designs while handling the categorization of seismic occurrences are presented in this part. When it is used with 11 neurons in the hidden layer, the performance is at its greatest. When the steepest descent is used to train the ANN with the functions of the tan sigmoid, the gradient may have a very tiny value of magnitude. Even if the weights and biases are fairly far from their ideal values, this leads to the lesser bias fluctuations and the weight vector.

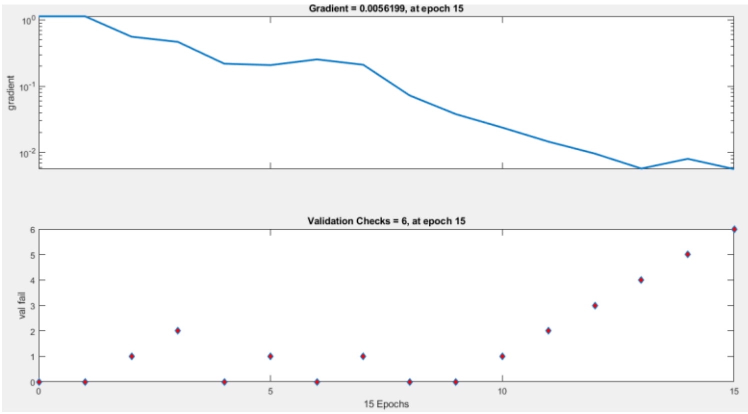

Figure 7 Neural Network Training State Epoch 6, Validation step

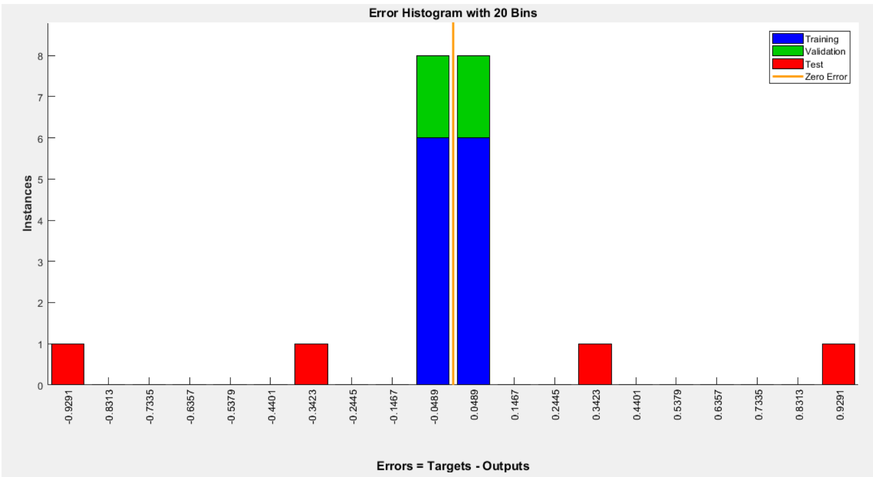

Figure 8 Neural Network Training Error Histogram

The histogram of errors between goal values and predicted values during feedforward neural network training is known as the error histogram. These error numbers may be negative since they show how the projected values and the goal values vary.

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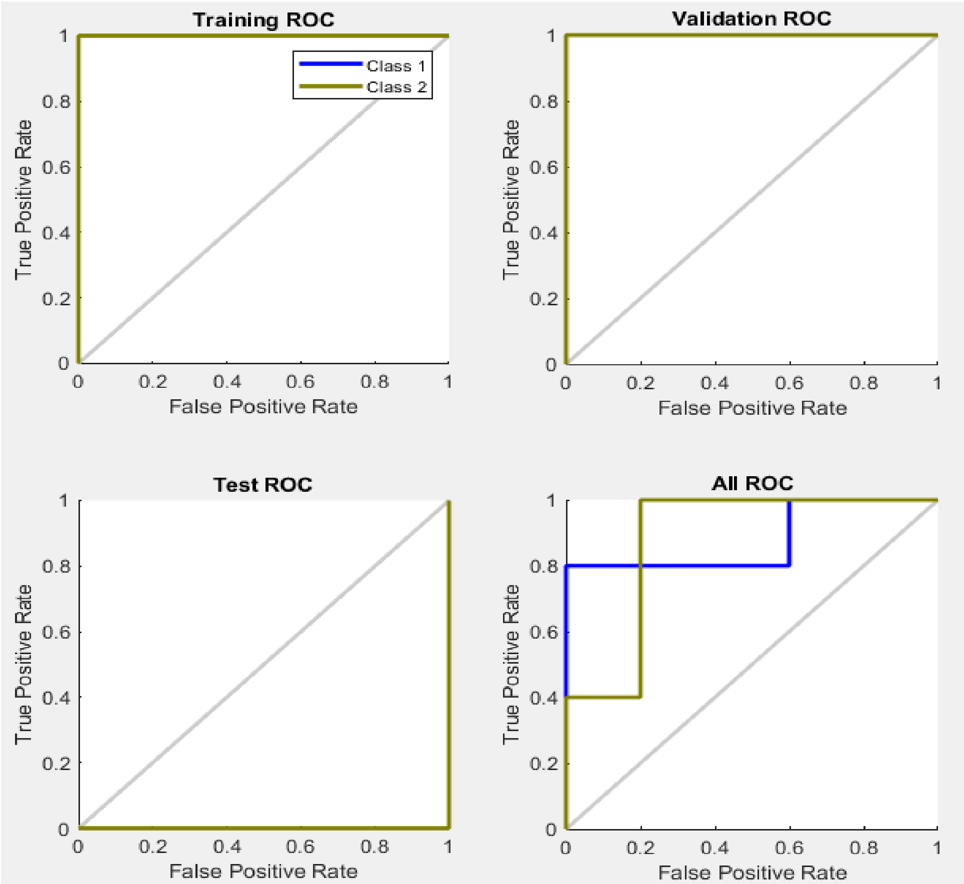

Figure 9 Receiver Operating Characteristics of Neural Network

The ROC (Receiver Operating Characteristics) curve is a plot of the performance of the model (a plot of the true positive rate and the false positive rate) at all classification thresholds. The AUC is the measurement of the entire two-dimensional area under the curve and as such is a measure of the performance of the model at all possible classification thresholds.

Table 1: Comparison of Results of classification using various machine learning techniques

PERFORMANCE METRICES						
TECHNIQUES	**ACCURACY**	**SENSITIVITY**	**PRECISION**	**RECALL**	**Kappa**	**MCC**
DWT-MLP (Proposed Methods)	**98%**	**97.7%**	**98.2%**	**97.9%**	**0.934**	**1**
SVM	**92%**	**94.5%**	**96%**	**94.2%**	**0.871**	**-0.8**
SVD	**91.5%**	**93%**	**92.1%**	**95.7%**	**0.734**	**-0.5**

CONCLUSION

The effectiveness of a DWT-MLP neural network for identifying seismic signals captured by the local seismic network of Newzealand was investigated in this paper. It was shown that the DWT-MLP classifier can identify the class of each signal using an acceptable level of accuracy using a set of signals utilised for assessment. In altogether, 98% of all the compared algorithms produced the best recognition rate for the suggested DWT-MLP.

REFERENCE

[1] João Paulo Canário, Rodrigo Mello, Millaray Curilem, Fernando Huenupan, Ricardo Rios, In-depth comparison of deep artificial neural network architectures on seismic events classification, Journal of Volcanology and Geothermal Research,Volume 401, 2020, 106881, ISSN 0377-0273, https://doi.org/10.1016/j.jvolgeores.2020.106881.

[2] E. Yıldırım, A. Gulbag, G. Horasan and E. Dogan: Discrimination of quarry blasts and earthquakes in the vicinity of Istanbul using soft computing techniques. Computers & Geosciences, 01-09, 2010.

[3] A. Fichtner, H. Tkal˘ci`c, Insights into the kinematics of a volcanic caldera drop: Probabilistic finite-source inversion of the 1996 b´ardarbunga, iceland, earthquake, Earth and Planetary Science Letters 297 (2010) 607–615.

[4] M. Curilem, C. Soto, F. Huenupan, C. San Martin, G. Fuentealba, C. Cardona, L. Franco, Improving the classification of volcanic seismic events extracting new seismic and speech features, in: Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications. CIARP 2017. Lecture Notes in Computer Science, volume 10657 of *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, Springer, Cham, 2017, pp. 177–185.

[5] M. van Gerven, S. Bohte, Artificial neural networks as models of neural information processing, Frontiers Media SA, 2018.

[6] S. Lapins, D. C. Roman, J. Rougier, S. D. Angelis, K. V. Cashman, J.-M. Kendall, An examination of the continuous wavelet transform for volcano-seismic spectral analysis, Journal of Volcanology and Geothermal Research 389 (2020) 106728.

[7] J. Soubestre, N. M. Shapiro, L. Seydoux, J. de Rosny, D. V. Droznin, S. Y. Droznina, S. L.Senyukov, E. I. Gordeev, Network-based detection and classification of seismovolcanic tremors: Example from the klyuchevskoy volcanic group in kamchatka, Journal of Geophysical Research: Solid Earth 123 (2018) 564–582

[8] Cui X, Huang H, Hao Y, Li L, Luo Y, Zeng J, Tian Z, Shen Y and Hu Y(2023) Supervised poststack 3D seismic data classification via multiscale and multilabel consistent feature reduction, *GEOPHYSICS*, 10.1190/geo2022-0517.1, 88:2, (N21-N37), Online publication date: 1-Mar-2023

[9] Jinyong Zhang, Ruochen Jiang, Biao Li, Nuwen Xu, An automatic recognition method of microseismic signals based on EEMD-SVD and ELM, Computers & Geosciences, Volume 133, 2019, 104318,ISSN 0098-3004, https://doi.org/10.1016/j.cageo.2019.104318.

[10] M. Ramkumar *et al* 2021 *J. Phys.: Conf. Ser.* 1831 012015**,**DOI 10.1088/1742-6596/1831/1/012015