DOI: https://doi.org/10.52756/ijerr.2023.v32.035 *Int. J. Exp. Res. Rev.*, Vol. 32: 398-407 (2023)

Original Article | Peer Reviewed | Open Access

International Journal of Experimental Research and Review (IJERR)

ISSN: 2455-4855 (Online)
www.iaph.in

Precision fault prediction in motor bearings with feature selection and deep learning

Deep Prakash Singh* and Sandip Kumar Singh

Department of Mechanical Engineering, VBS Purvanchal University, Jaunpur, UP, India

E-mail/Orcid Id:

DPS, deepprakashsinghvbspu@gmail.com, https://orcid.org/0009-0008-8931-0393;

SKS, sandipkumarsingh25@gmail.com

Article History:

Received: 18th April., 2023
Accepted: 22nd Aug., 2023
Published: 30th Aug., 2023

Keywords:
Convolutional Neural Network, Feed Forward Neural Network and Radial Based Network, Correlation and Chi-Square.

Abstract: In the disciplines of industrial machinery, mechanical engineering is beneficial to recognize motor performance for motors with HP power, torque transducer, dynamometer, and control electronics. The motivation is to address the need for more accurate and efficient fault prediction in machinery to prevent breakdowns, reduce maintenance costs, and improve overall reliability. In this work, deep learning classifiers used to classify ball defect inner race fault, outer race fault and normal motor performance in testing. With the aid of three distinct classifiers CNN, FFNN, and RBN; these suggested relative characteristics are assessed. In comparison to other current algorithms, the suggested methodology for classifying motor performance achieved maximum accuracy in each CNN test at 95.4% and 97.7%. The correlation and chi-square algorithms are used to find out the added characteristics and rank of features. The correlation technique provides relations between attributes, and the chi-square offers the optimal balance between precision and feature space. We discovered that the performance is enhanced overall by relative power characteristics. The suggested models might offer rapid responses with less complexity.

Introduction

Natural neural networks are a technique in deep learning. Due to the non-invasive, affordable and helpful nature of motor performance, impulses are frequently employed as input for motor sensors (Yuan and He, 2014).

Regarding the motor sensor, some observations calculate similarities for real movements compared to motor performance. The potential values of the device are changed after some activity. In various terms, motor sensors focus on different physical activities as physical motion (Bonassi et al., 2017; Munzert et al., 2009; Coyle et al., 2015; Anderson and Lenz, 2011; Phothisonothai and Nakagawa, 2008).

In general, the steps in this procedure are as follows: Prior to removing undesired frequency ranges pre-processing is employed. To finish feature extraction, several mapping models are constructed for distinct feature categories. The various feature models are then categorized and decoded separately. The conventional approach necessitates many steps. The processing results will be affected if there is a requirement to rectify an intermediate step. The challenge of pattern recognition arises from the inherent complexity of analysing the minute and intertwined nature of the gathered motor sensor data (Schlögl et al., 2010; Song et al., 2013; Vidaurre et al., 2007; Woehrle et al., 2015; Duan et al., 2019).

Deep neural networks (DNNs) have recently shown that they can successfully classify linguistic data, pictures, sounds, and natural texts. There are several benefits of using neural networks to decode motor sensor data. Nevertheless, due to limitations on the number of available participants, the experiment's length, and the technique's complexity, it is challenging to gather enough data for practical applications. The quantity of samples has a substantial impact on how effectively DNNs work. When training a model, small-scale datasets typically result in poor generalizability, negatively impacting classification accuracy (Song et al., 2017; Alom et al., 2018; Zhong et al., 2015; Cooney et al., 2019).

We evaluate CNN, RBFN, and FFNN in this post using a variety of characteristics. The results show that

*Corresponding Author: deepprakashsinghvbspu@gmail.com

NN was a successful method for categorizing motor bearings data; the proposed hybrid NN model outperformed the best method previously described in the literature.

Related work

We located the primary studies using the quality criterion. We highlighted these fundamental discoveries utilizing machine learning techniques, datasets, assessment metrics, and real-time monitoring of security breaches. The results demonstrate the necessity for more data preparation approaches to increase the standard of open datasets. Hybrid deep learning models must be employed if model detection performance continues to increase.

Although time-consuming and difficult, dataset pre-processing and aberrant traffic identification using ML algorithms are utilized in intrusion detection systems (Ferrag et al., 2021), nevertheless, employing more separate feature spaces and DL techniques may map features more precisely (Thapa et al., 2021). A CNN is a deep learning method that automatically extracts meaningful features from the feature plane of actual data using a convolution layer. For deep learning models, the best hyperparameters must be picked (Ahmed et al., 2022). The two primary methods for hyperparameter tuning are automated and hand-search strategies. While using the manual setup approach, selecting a lovely network structure at random is challenging. Automatically modifying hyperparameters for the ideal model structure is challenging. Uncertainty surrounds the optimization problem's target function when changing the hyperparameters. It is not possible to use standard optimization methods, such as Newton's method or gradient descent (Abdelmoumin et al., 2021). The hyperparameters of deep learning models may be optimized using algorithms.

Caroline et al. (2014) evaluated hyperparameters for solid connections and generated optimization techniques. They find F1-score increases up to 0.90 as a result. Tridawati et al. (2020), observed hyperparameters and a number of neurons. They found an accuracy rate of 97% in the results. Lee et al. (2018) used feature extraction for better performance of CNN. Authors used CNN for image recognition and trained the boost model of CNN as a powerful computational model. Wu et al. (2019) analyzed hyperparameters using a Bayesian algorithm and identified superior hyperparameters, which provide better results for algorithms. They used a combined model random forest with a neural network and calculated better results.

Amirabadi et al. (2020) organized a deep learning model with hyperparameters and calculated better-optimized results than other algorithms. Nonetheless, the outcomes show a notable decrease in computational complexity.

The best face recognition network to recognise faces in pictures with significant noise and occlusion, according to Lokku et al. (2022), was shown to be a CNN-based classifier. This research's main objective was to focus on hyperparameters and selected features using deep learning-based algorithms. Elmasry et al. (2020) used various deep learning algorithms for a single process with optimization techniques to find better results in hyper-tuning. Sakr et al. (2019), organized an SVM algorithm with an optimization technique for smart particles and calculated better results compared to previous algorithms. Alharbi et al. (2021) focused on hyperparameters using various neural network algorithms. They used algorithms for IOT threat detection and calculated good results for accuracy.

Ali et al. (2022) organized GWO technique to detect hyperparameters for algorithms. They experimented on false positive rates using deep neural networks with random forest and calculated better results compared to previous work. Vartouni et al. (2018) organized a random forest model and performed better results compared to other used algorithms.

Methodology

The dataset represents the motor performance of motor bearings. With the help of machine learning algorithms, we detect important features ranking as correlation and chi-square to determine the most essential characteristic and assess the applicability of each technique. Using the specified classification procedures, all feature sets and ranking feature sets have been classified. Accuracy is used to evaluate the results. For the same dataset, the results are also contrasted with those of previous methods.

Dataset description

Few datasets are committed explicitly to using machine learning in the industrial field of mechanical engineering. The test bearings support the motor shaft. EDM machining introduced flaws in a particular location. Any flaw present in one of the ball, inner race, or outer races of the bearing has a time series.

To execute the fault detection prediction, the following 9 characteristics must be calculated: maximum, minimum, mean, standard deviation, RMS, skewness, kurtosis, crest factor, and form factor. Each feature is calculated for 2048-point time segments (0.04 seconds at the 48kHz accelerometer sampling frequency). This dataset is visualized in Figure 1, and is publicly available thanks to Case Western Reserve University (https://case.edu/).

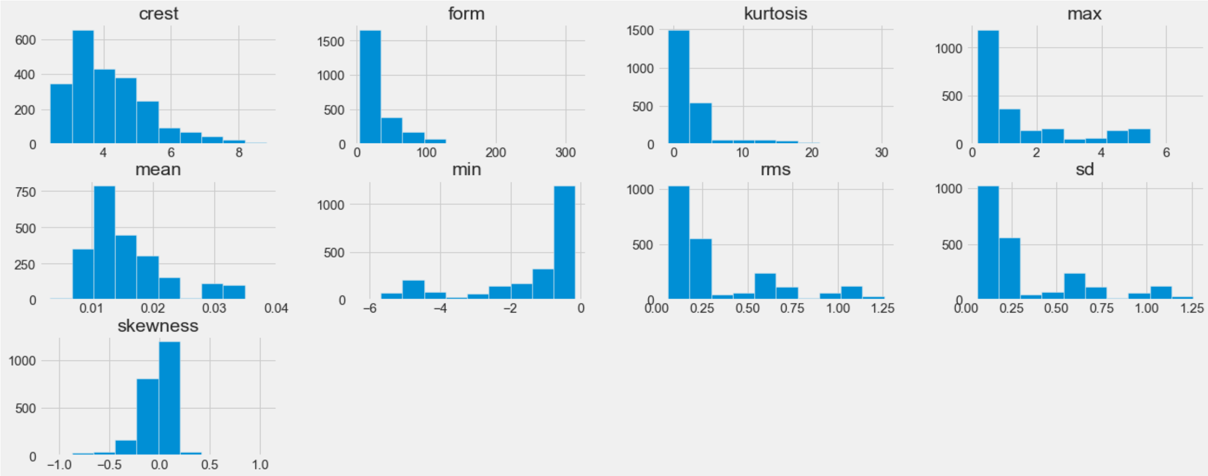

Figure 1. Representation of motor bearing dataset

The significance of the proposed characteristics that are employed in the work is assessed with the use of feature ranking algorithms. The most popular feature ranking techniques are correlation and chi-square. These two methods are employed in this study to identify the most crucial and least crucial traits.

Comparative analysis is done using the feature ranking approach. The feature ranking approach is further explained in the next section.

Algorithms description

Convolutional neural network

The Convolutional Neural Network is used for object (pictures or images, etc.) identification. This algorithm uses various weight layers for better results in object prediction in Figure 2.

The CNN technique does not require high-level data classification preprocessing whenever other neural networks require high-level preprocessing.

Feed-forward neural networks

Many layers of function compositions are sequentially arranged in a feed-forward neural network. Each layer produces a collection of vectors that the subsequent layer, which is a set of functions, uses as input. Three different layers exist in Figure 3.

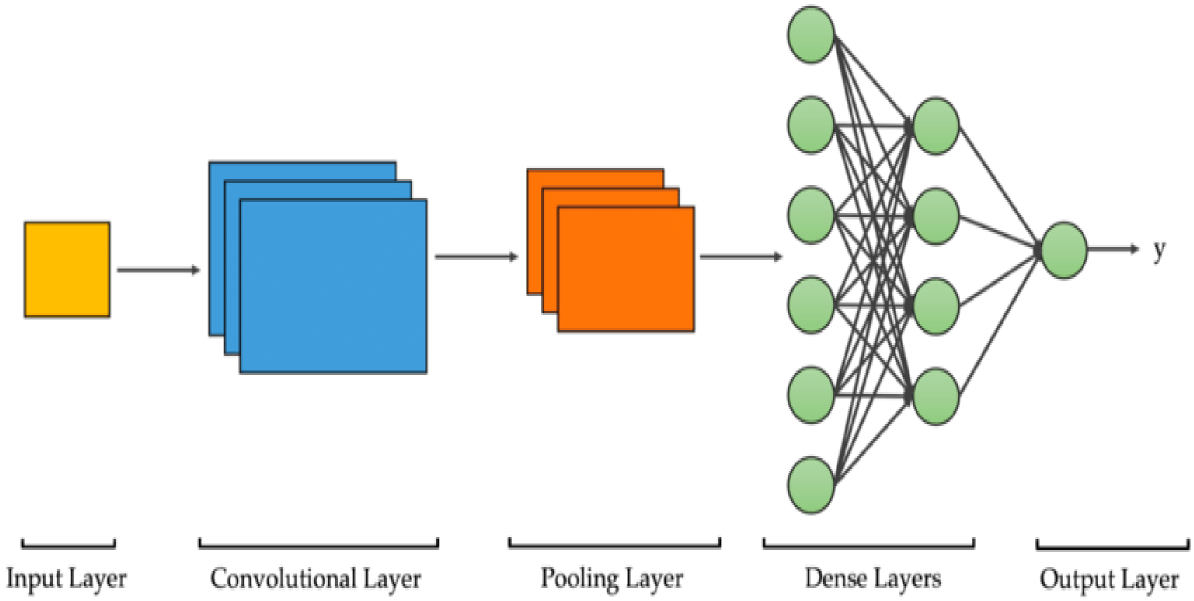

Figure 2. Representation of convolutional neural network (Parra et al., 2020)

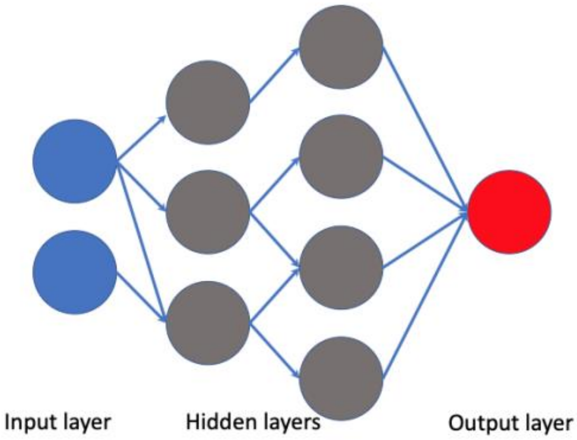

Figure 3. Representation of feed-forward neural network (Alzubaidi et al., 2021)

- Raw input data is referred to as the input layer.
- Hidden layer(s) are a series of functions applied to the inputs or outputs of earlier hidden layers.
- Last function or collection of functions in the output layer.

The blue nodes here reflect the raw data input layer (circles). Grey nodes, often referred to as "neurons," make up the hidden layers; each neuron takes in the nodes from the layer above, which is linked as input and outputs some value. The red node creates the output layer, which is the final function.

Consider the output layer as the final model that inputs the last hidden layer as one method of approaching this. The following hidden layers learn and then improve the qualities of the raw inputs.

Radial basis function network

An example of a neural network that integrates to address non-linear classification problems is the Radial Basis Function Network or RBFN for short. RBFNs differ from traditional multilayer perceptron networks in that they do not simply multiply an input vector by a coefficient and add the results. As an alternative, RBFNs evaluate each input vector, contrast the input with the stored training value, and calculate a similarity score. The sum is the output layer when each similarity value has been multiplied by weights. It is easy to compute every new input by computing the Euclidean distance between the new input and training data in Figure 4.

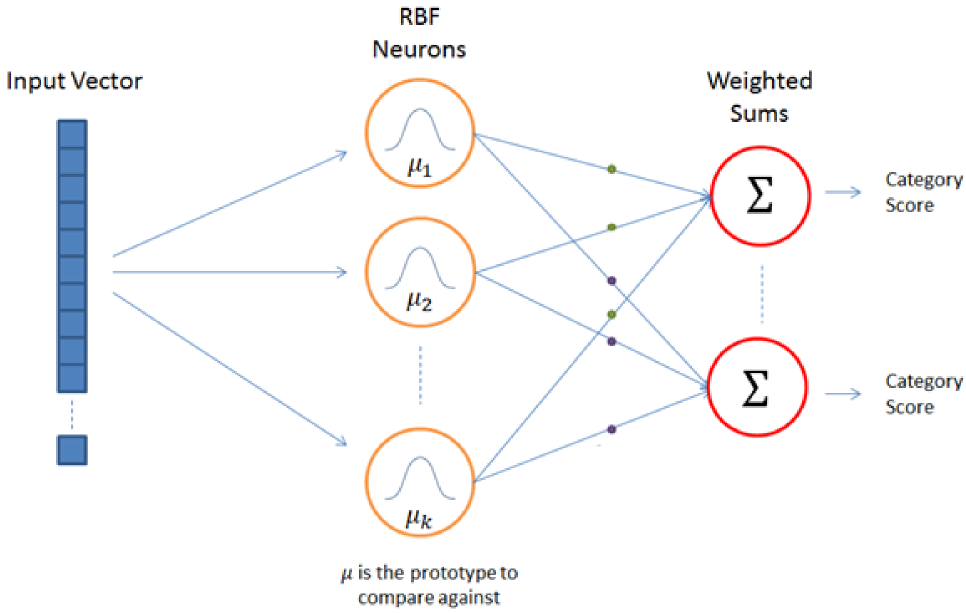

Figure 4. Representation of radial basis function network (Gabrié et al., 2018)

DOI: https://doi.org/10.52756/ijerr.2023.v32.035

This study focuses on the evaluation of motor bearing performance in order to effectively regulate motor performance. The relative attributes under consideration are assessed using three distinct classifiers, namely Convolutional Neural Network (CNN), Feed Forward Neural Network (FFNN), and Randomised Boolean Network (RBN). This study aims to evaluate the significance of recently introduced attributes of features using the Chi-square test and identify reliable correlation features in motor-bearing tasks.

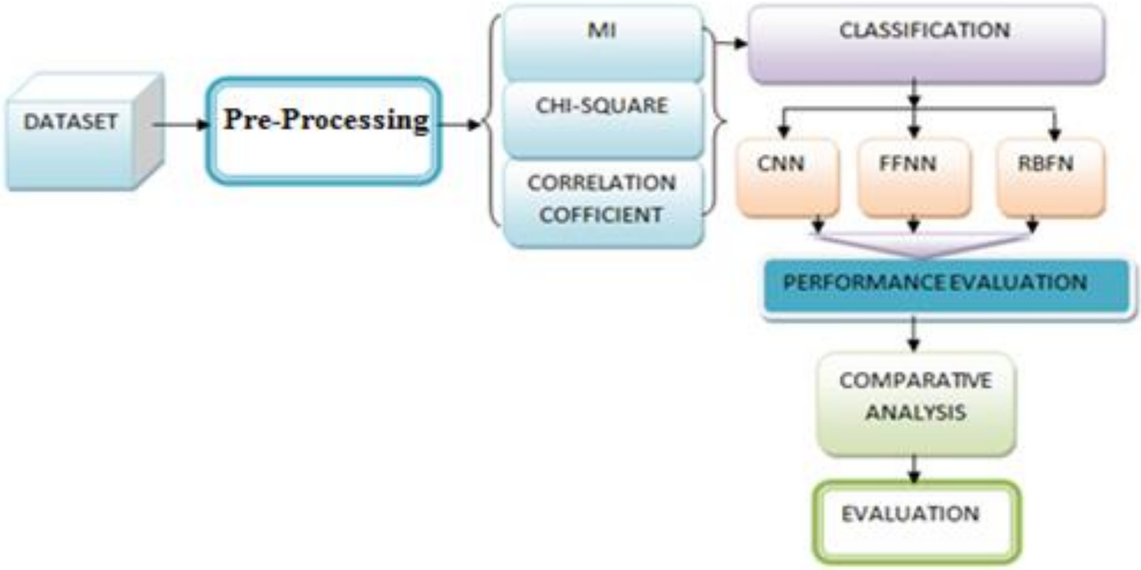

Figure 5. Representation of the proposed model

The approach produces a feature matrix, input into several classifiers to gauge how well the features work. Three well-known classifiers—CNN, RBN, and FFNN—are employed for classification.

In Section 3, the findings of the classification are displayed and explained. The classification outcomes are examined based on the classifiers' classification accuracy. Analysis of the current research in comparison to other existing.

Results

In this research, we have selected the motor bearing dataset for their task prediction as classification and compare task accuracy in various experiments.

Experimental model without feature ranking

Three classifiers—CNN, RBN, and FFNN—that are among the most frequently used classifiers are utilized in this study to categorize motor bearing tasks. The findings are displayed in Table 1.

Bold letters indicate the classifiers' highest level of classification accuracy. CNN splits the input and makes a conclusion based on experience; it functions like the human brain. The findings show that, except CNN, all classifiers offer competitive accuracy. The CNN classifier's best accuracy score is 90.8%.

Experimental results with Chi-Square for features ranking

The ranking of characteristics is determined using the chi-square test. The rank values of attributes decide the status of attributes in the class (Hussein and Özyurt, 2021).

Figure 6 displays the Chi-square test results for 10 characteristics in the experiment. Another well-liked way of choosing features is the chi-square method. The exact process is used in the current study, and the high ranker's four features are selected from eleven features by the chi-square approach. Figure 6 represents the outcomes of the feature selection process after 10 iterations. The top four characteristics are chosen based on how frequently they appear throughout revisions. For further experiments, we observed the features "7, 2, 8 and 4" are chosen as the most essential features.

Experimental results with correlation for features ranking

The correlation method, as proposed by Yuan et al. (2020), is an additional metric for feature ranking that provides information on the interconnectedness of characteristics. Figure 7 displays the heat map of the characteristics of the 10 features.

Darker colors in the heat map indicate a better correlation, whereas lighter colors indicate a lower correlation among the features. Figure 7 displays the correlated pairs that the correlation feature selection module produced after 10 iterations. The associated feature pairs are displayed in Figure 7. The less important a feature is, the stronger the correlation; as a result,

Table 1. Computational accuracy model for different algorithms

Iterations	Convolutional Neural Network	Feed Forward Neural Network	Radial Based Network
1	90.1	87.3	63.4
2	89.2	85.2	68.6
3	90.1	87.4	69.1
4	88.7	86.3	65.2
5	89.9	83.4	64.2
6	88.3	85.8	56.5
7	87.2	86.8	67.1
8	89.4	84.8	62.5
9	**90.8**	**90.1**	**71.8**
10	90.1	89.3	65.6
AVG	89.4	86.6	65.4

	Specs	Score
7	crest factor	650.01
2	mean	217.82
8	form factor	130.47
4	RMS	110.72
0	maximum	81.43
3	standard deviation	45.97
1	minimum	24.37
6	kurtosis	9.74
5	skewness	1.48

Figure 7. Feature rankings with the Chi-square method

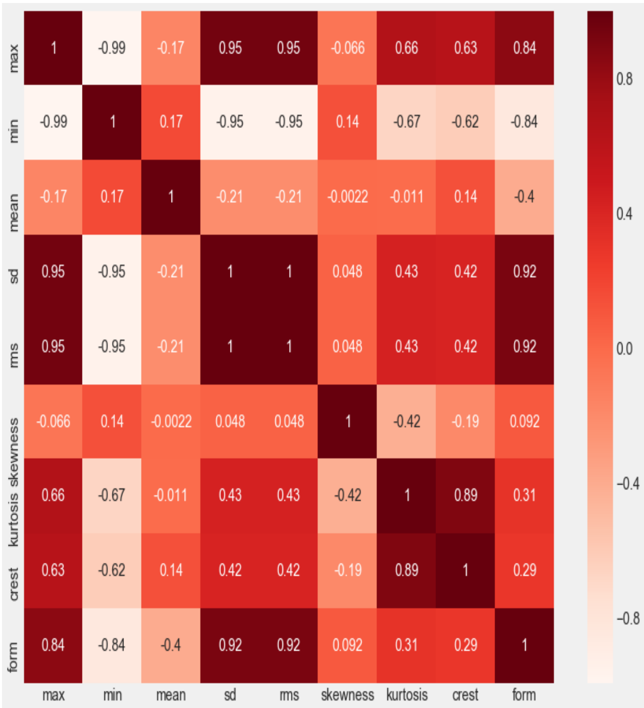

Figure 6. Representation of ten subjects by heat map

characteristics max, min, and mean can be regarded, and accuracy can be determined among the features for further research. This also demonstrates that the aspects of relative power, specifically other features, do not correlate. This illustrates the importance of relative power attributes about their connection.

Experimental results of overall analysis for features ranking

The experimental results of the overall analysis for features ranking effect on classification accuracy for motor bearing tasks are described in this section. The accuracy has been determined by considering the top features found using the feature ranking approach. The outcomes are displayed in Table 1.

An important finding is that the average accuracy of 90.8% has been attained when all characteristics are considered. We examine the significance of relative power attributes by measuring the accuracy without considering them. The research also excludes the remaining features in favour of the top features from various ranking algorithms depending on rank. The outcomes of dropping specific characteristics do not impact the accuracy of the classification. The following section offers a comparison of several existing models and feature ranking techniques (Banerjee et al., 2023; Reddy and Khanna, 2023; Rao et al, 2023).

Discussion

The influence of relative power and power variance is considered for categorising motor bearing tasks in the current study. The proposed method for categorizing motor bearing tasks is evaluated in the context of ten iterations. The results show that the proposed technique performs better for classification due to the nature of correlated pairs of features across all parameters.

This experiment determines the outcomes using three methods linked to characteristics: correlation and chi-square. The average dataset accuracy for each experiment was calculated after it had been carried out three times as T1, T2, and T3. According to a comparison of various techniques of features, we calculate Chi-square analysis utilizing the feature set of 7, 2, 8 and 4, results in an average accuracy of 95.4%. Once more, the critical selected features are calculated with an average accuracy of 97.7% and show the most negligible correlation in the correlation-based method. So, these proposed qualities are crucial in other situations where it is believed that Chi-Square and feature correlation are the fundamental problems, in addition to enhancing accuracy. The research also illustrates a trade-off between accuracy and feature space complexity when complexity is the main issue.

Table 2. Computational model for analysis of accuracy

Features Methods	Analysis	Convolutional Neural Network	Feed Forward Neural Network	Radial Based Network
Chi-Square	T1	95.7	94.2	93.7
	T2	95.2	94.7	94.2
	T3	95.2	94.4	95.2
	Avg.	**95.4**	**94.4**	**94.3**
Correlated	T1	95.7	93.8	93.7
	T2	97.1	94.3	95.2
	T3	97.3	97.5	97.3
	Avg.	**97.7**	**95.2**	**95.4**

Conclusion

Significant progress has been achieved in the field of motor bearing as a result of various complex model analysis. Based on the obtained data, it was observed that the three employed classifiers yielded the most favorable outcomes. The suggested methodology mitigates the issue of unpredictability in attribute iterations while still preserving the tradeoff and complexity. The indicated relative qualities are tested using three separate classifiers: Convolutional Neural Network (CNN), Feedforward Neural Network (FFNN), and Randomized Boolean Network (RBN). The proposed approach for categorizing motor performance in motor bearings demonstrated superior accuracy in comparison to other contemporary methods, achieving maximum accuracies of 95.4% and 97.7%.

The feature rating technique evaluates the significance of newly added qualities. In conclusion, the ranking algorithms provide satisfactory performance. However, when evaluating the comparison of the outcomes, it is seen that the feature exhibits an average accuracy of 97.7% in the correlation-based technique, indicating the lowest correlation. Nevertheless, in terms of the accuracy of the approach for motor bearing analysis, the inclusion of the relative power factor enhances the overall effectiveness of the system. Subsequent investigations

DOI: https://doi.org/10.52756/ijerr.2023.v32.035

will be predicated around the utilization of motor sensor pictures, hence expanding the scope of inquiry to encompass issues pertaining to the positioning and selection of electrodes, enhancement of signal-to-noise ratio, and mitigation of device reliance.

Data Availability

Publicly available datasets are used in this research, which was accessed via https://case.edu/.

Conflict of interest

The authors assert that there are no competing interests evident in this study.

References

Abdelmoumin, G., Rawat, D. B., & Rahman, A. (2021). On the performance of machine learning models for anomaly-based intelligent intrusion detection systems for the internet of things. *IEEE Internet of Things Journal*, *9*(6), 4280-4290. https://doi.org/10.1109/JIOT.2021.3103829.

Ahmed, N., Ngadi, A. B., Sharif, J. M., Hussain, S., Uddin, M., Rathore, M. S., ... & Zuhra, F. T. (2022). Network threat detection using machine/deep learning in sdn-based platforms: a comprehensive analysis of state-of-the-art solutions, discussion, challenges, and future research direction. *Sensors*, *22*(20), 7896. https://doi.org/10.3390/s22207896 PMID: 36298244

Alharbi, A., Alosaimi, W., Alyami, H., Rauf, H. T., & Damaševičius, R. (2021). Botnet attack detection using local global best bat algorithm for industrial internet of things. *Electronics*, *10*(11), 1341. https://doi.org/10.3390/electronics10111341.

Ali, M. H., Jaber, M. M., Abd, S. K., Rehman, A., Awan, M. J., Damaševičius, R., & Bahaj, S. A. (2022). Threat analysis and distributed denial of service (DDoS) attack recognition in the internet of things (IoT). *Electronics*, *11*(3), 494. https://doi.org/10.3390/electronics11030494.

Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., ... & Farhan, L. (2021). Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. *Journal of big Data*, *8*, 1-74. https://doi.org/10.1186/s40537-021-00444-8.

Alom, M. Z., Taha, T. M., Yakopcic, C., Westberg, S., Sidike, P., Nasrin, M. S., ... & Asari, V. K. (2018). The history began from alexnet: A comprehensive survey on deep learning approaches. *arXiv preprint arXiv:1803.01164*. https://doi.org/10.48550/arXiv.1803.01164.

Amirabadi, M. A., Kahaei, M. H., & Nezamalhosseini, S. A. (2020). Novel suboptimal approaches for hyperparameter tuning of deep neural network [under the shelf of optical communication]. *Physical Communication*, *41*, 101057. https://doi.org/10.1016/j.phycom.2020.101057.

Anderson, W. S., & Lenz, F. A. (2011). Review of motor and phantom related imagery. *Neuroreport*, *22*(17), 939.

Banerjee, M., Goyal, R., Gupta, P., & Tripathi, A. (2023). Real-Time Face Recognition System with Enhanced Security Features using Deep Learning. *International Journal of Experimental Research and Review*, *32*, 131-144. Retrieved from https://qtanalytics.in/journals/index.php/IJERR/article/view/2488

Bonassi, G., Biggio, M., Bisio, A., Ruggeri, P., Bove, M., & Avanzino, L. (2017). Provision of somatosensory inputs during motor imagery enhances learning-induced plasticity in human motor cortex. *Scientific reports*, *7*(1), 9300.

Caroline Müllenbroich, M., McGhee, E. J., Wright, A. J., Anderson, K. I., & Mathieson, K. (2014). Strategies to overcome photobleaching in algorithm-based adaptive optics for nonlinear in-vivo imaging. *Journal of Biomedical Optics*, *19*(1), 016021-016021. https://doi.org/10.1117/1.JBO.19.1.016021.

Cooney, C., Folli, R., & Coyle, D. (2019, October). Optimizing layers improves CNN generalization and transfer learning for imagined speech decoding from EEG. In *2019 IEEE international conference on systems, man and cybernetics (SMC)* (pp. 1311-1316). IEEE. https://doi.org/10.1109/SMC.2019.8914246.

Coyle, D., Stow, J., McCreadie, K., McElligott, J., & Carroll, Á. (2015). Sensorimotor modulation assessment and brain-computer interface training in disorders of consciousness. *Archives of physical medicine and rehabilitation*, *96*(3), S62-S70.

Duan, X., Xie, S., Xie, X., Meng, Y., & Xu, Z. (2019). Quadcopter flight control using a non-invasive multi-modal brain computer interface. *Frontiers in neurorobotics*, *13*, 23.

Elmasry, W., Akbulut, A., & Zaim, A. H. (2020). Evolving deep learning architectures for network intrusion detection using a double PSO metaheuristic. *Computer Networks*, *168*, 107042. https://doi.org/10.1016/j.comnet.2019.107042

Ferrag, M. A., Shu, L., Djallel, H., & Choo, K. K. R. (2021). Deep learning-based intrusion detection for distributed denial of service attack in agriculture 4.0. *Electronics*, *10*(11), 1257. https://doi.org/10.3390/electronics10111257.

Gabrié, M., Manoel, A., Luneau, C., Macris, N., Krzakala, F., & Zdeborová, L. (2018). Entropy and mutual information in models of deep neural networks. *Advances in Neural Information Processing Systems*, *31*.

Hussein, M., & Özyurt, F. (2021). A new technique for sentiment analysis system based on deep learning using Chi-Square feature selection methods. *Balkan Journal of Electrical and Computer Engineering*, *9*(4), 320-326.

Lee, W. Y., Park, S. M., & Sim, K. B. (2018). Optimal hyperparameter tuning of convolutional neural networks based on the parameter-setting-free harmony search algorithm. *Optik*, *172*, 359-367. https://doi.org/10.1016/j.ijleo.2018.07.044.

Lokku, G., Reddy, G. H., & Prasad, M. G. (2022). OPFaceNet: OPtimized Face Recognition Network for noise and occlusion affected face images using Hyperparameters tuned Convolutional Neural Network. *Applied Soft Computing*, *117*, 108365. https://doi.org/10.1016/j.asoc.2021.108365.

Munzert, J., Lorey, B., & Zentgraf, K. (2009). Cognitive motor processes: the role of motor imagery in the study of motor representations. *Brain research reviews*, *60*(2), 306-326.

Parra, G. D. L. T., Rad, P., Choo, K. K. R., & Beebe, N. (2020). Detecting Internet of Things attacks using distributed deep learning. *Journal of Network and Computer Applications*, *163*, 102662. https://doi.org/10.1016/j.jnca.2020.102662.

Phothisonothai, M., & Nakagawa, M. (2008). EEG-based classification of motor imagery tasks using fractal dimension and neural network for brain-computer interface. *IEICE TRANSACTIONS on Information and Systems*, *91*(1), 44-53.

Rao, M., Kumar, S., & Rao, K. (2023). Effective medical leaf identification using hybridization of GMM-CNN. *International Journal of Experimental Research and Review*, *32*, 115-123. Retrieved from https://qtanalytics.in/journals/index.php/IJERR/article/view/2486

Reddy, N. S., & Khanaa, V. (2023). Diagnosing and categorizing of pulmonary diseases using Deep learning conventional Neural network. *International Journal of Experimental Research and Review*, *31*(Spl Volume), 12-22. https://doi.org/10.52756/10.52756/ijerr.2023.v31spl.002

Sakr, M. M., Tawfeeq, M. A., & El-Sisi, A. B. (2019). Network intrusion detection system based PSO-SVM for cloud computing. *International Journal of Computer Network and Information Security*, *11*(3), 22. https://doi.org/10.5815/ijcnis.2019.03.04

Schlögl, A., Vidaurre, C., & Müller, K. R. (2010). Adaptive methods in BCI research-an introductory tutorial. Berlin, Heidelberg: Springer Berlin Heidelberg. In *Brain-Computer Interfaces: Revolutionizing Human-Computer Interaction*, pp. 331-355.

Song, X., Shibasaki, R., Yuan, N. J., Xie, X., Li, T., & Adachi, R. (2017). DeepMob: learning deep knowledge of human emergency behavior and mobility from big and heterogeneous data. *ACM Transactions on Information Systems (TOIS)*, *35*(4), 1-19.

Song, X., Yoon, S. C., & Perera, V. (2013, November). Adaptive common spatial pattern for single-trial EEG classification in multisubject BCI. In *2013 6th International IEEE/EMBS Conference on Neural Engineering (NER)* (pp. 411-414).

Thapa, N., Liu, Z., Shaver, A., Esterline, A., Gokaraju, B., & Roy, K. (2021). Secure cyber defense: An analysis of network intrusion-based dataset CCD-idsv1 with machine learning and deep learning models. *Electronics*, *10*(15), 1747. https://doi.org/10.3390/electronics10151747.

Tridawati, A., Wikantika, K., Susantoro, T. M., Harto, A. B., Darmawan, S., Yayusman, L. F., & Ghazali, M. F. (2020). Mapping the distribution of coffee plantations from multi-resolution, multi-temporal, and multi-sensor data using a random forest algorithm. *Remote Sensing*, *12*(23), 3933.

Vartouni, A. M., Kashi, S. S., & Teshnehlab, M. (2018, February). An anomaly detection method to detect web attacks using stacked auto-encoder.

In *2018 6th Iranian Joint Congress on Fuzzy and Intelligent Systems (CFIS)*, pp. 131-134. https://doi.org/10.1109/CFIS.2018.8336654.

Vidaurre, C., Schlogl, A., Cabeza, R., Scherer, R., & Pfurtscheller, G. (2007). Study of on-line adaptive discriminant analysis for EEG-based brain computer interfaces. *IEEE transactions on biomedical engineering*, *54*(3), 550-556.

Woehrle, H., Krell, M. M., Straube, S., Kim, S. K., Kirchner, E. A., & Kirchner, F. (2015). An adaptive spatial filter for user-independent single trial detection of event-related potentials. *IEEE Transactions on Biomedical Engineering*, *62*(7), 1696-1705.

Wu, J., Chen, X. Y., Zhang, H., Xiong, L. D., Lei, H., & Deng, S. H. (2019). Hyperparameter optimization for machine learning models based on Bayesian optimization. *Journal of Electronic Science and Technology*, *17*(1), 26-40. https://doi.org/10.11989/JEST.1674-862X.80904120.

Yuan, H., & He, B. (2014). Brain–computer interfaces using sensorimotor rhythms: current state and future perspectives. *IEEE Transactions on Biomedical Engineering*, *61*(5), 1425-1435.

Yuan, X., Ou, C., Wang, Y., Yang, C., & Gui, W. (2020). Deep quality-related feature extraction for soft sensing modeling: A deep learning approach with hybrid VW-SAE. *Neurocomputing*, *396*, 375-382. https://doi.org/10.1016/j.neucom.2018.11.107.

Zhong, Z., Jin, L., & Xie, Z. (2015, August). High performance offline handwritten chinese character recognition using googlenet and directional feature maps. In *2015 13th International Conference on Document Analysis and Recognition (ICDAR)*, pp. 846-850. https://doi.org/10.1109/ICDAR.2015.7333881.

How to cite this Article:

Deep Prakash Singh* and Sandip Kumar Singh (2023). Precision fault prediction in motor bearings with feature selection and deep learning. *International Journal of Experimental Research and Review*, *32*, 398-407.

DOI : https://doi.org/10.52756/ ijerr.2023.v32.035