Fault Prediction Using Fuzzy Convolution Neural Network on IoT Environment with Heterogeneous Sensing Data Fusion

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Abstract. The data was subsequently used to develop a non-contact vibration pickup from the rotating machinery, within a specified load and speed conditions, and thus ensure timely detection of bearing defects. The collected vibration data was denoised through the Hilbert transform. Dimensionality reduction was performed using Principal Component Analysis (PCA), followed by a sequential floating forward selection (SFFS) process to identify the most relevant features. SVM and ANN were used for detecting and classifying different bearing faults using selected features. This colonial way of functioning not only reduces the time and effort involved in piping maintenance, but in the long run, also saves a considerable amount of finances too.

Keywords: Machine Learning, Performance Evaluation, Reliability, Fault Bearings.

1 Introduction

The increasing global market demand for sustainable energy, solar photovoltaic (PV) technology, has emerged as a significant source of renewable energy. However, ensuring that photovoltaic modules work properly is vital for the long-term reliability and efficiency of photovoltaic systems. Identifying and repairing defective PV modules is essential for maximising energy output and system reliability. Or common monitoring and maintenance approaches fail to catch small or emerging solar array issues. Machine learning algorithms can be implemented to fix this issue and detect broke solar modules on time and accurately. By leveraging strong data analytics and pattern recognition, these algorithms have the potential to scan through massive flows of performance data, allowing for pro-active anomaly detection and preventative maintenance. A next level of robustness and performance in photovoltaic systems is solar technology and artificial intelligence with one step earlier.

1.1 Machine Learning

Machine learning, a subset of artificial intelligence, has transformed how we tackle challenging problems across diverse domains. It is a technique that allows computers to learn from data by itself and make decisions or predictions without having to be programmed with specific rules or instructions. Various industries adopted this revolutionary technology such as healthcare, banking, autonomous automobiles, and natural language processing. Fundamentally, machine learning depends on models and algorithms capable of processing and detecting patterns in enormous datasets to derive solutions that were once only imaginable from science fiction.

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S. Kannadhasan et al. (eds.), Proceedings of the International Conference on Sustainability Innovation in Computing and Engineering (ICSICE 24), Advances in Computer Science Research 120,
https://doi.org/10.2991/978-94-6463-718-2_53

Making sense of the massive and complex amount of data we have in this age of data abundance. In tasks such as identifying pictures, translating languages and even playing games, it often does so better than humans. With new algorithm development, increasing processing power, and abundance of enormous datasets, machine learning has flourished. This has resulted in some incredible accomplishments; however, this has also come with a new set of challenges. We trust machine learning with crucial decisions, from autonomous driving to medical diagnostics, so we must understand what he is capable of, and what he needs. Deep fake algorithms, naturally a lot of issues can arise due to them and they are but one part of a very vast field as it is likened to a universe in which there are galaxies and stars and one of those galaxies are algorithms that are played out every day the universe is dynamic and the figures of this universe affect our daily lives and at the end the chapter explains that with the rise of opportunity and potential a lot of problems arise too with it and we on behalf of governance should work to mitigate in different aspects to solve these issues in this new interaction paradigm ranging from ethical to social-political-science and finally-even-technical-cohomology grounds of things.

1.2 Performance Evaluation

Performance evaluation is a basic and well-known methodology that offers a structured approach for the evaluation for the performance, efficiency, as well as the overall quality of systems, processes and outcomes. Performance evaluation is a critical tool for decision-making and continuous improvement in various fields, including business, healthcare, education, and technology. It encompasses the systematic collection, analysis and interpretation of relevant data to determine the extent to which objectives and expectations are met, identify opportunities for improvement, and inform strategies that lead to the greatest outcomes. Now, with data playing an even more critical role in performance measurement, assessments are changing faster than ever before as new metrics, tools, and processes emerge to help drive broader and deeper evaluation to impact a range of industries. The need for performance evaluation has acquired special importance, particularly when on one hand individuals, and on the other hand, organizations are striving to extract the utmost of their endeavors. We present in this introduction the complex world of performance evaluation; we highlight the importance of the subject and its use in different settings. We will discuss the techniques, KPIs, and best practices that form the foundation of this essential profession and how it is changing to meet the demands of our new globalised society. As long as we understand performance review and leverage its impact, we can aspire for excellence and improve decision-making.

1.3 Reliability

Markov is a distinctive measurement of reliability that is used in various domains like engineering, technology, healthcare, transportation, etc., and it is essential for the dependability of products, processes, and systems. Reliability is the ability of a system to provide its intended service being constantly operational over a given period of time and under certain conditions without failure, error or breakdown. Reliable systems help things run smoothly and consistently in a world in which safety and security matter. Because the reliability of a digital service, medical device or industrial machine directly affects people's safety, financial security and quality of life. Before explaining in detail, the concept of reliability, this section acts as a preface to the remainder of the discussion, highlighting the universal significance of reliability as well as the general necessity of ensuring reliability in various systems.

We'll look at how engineers, designers and practitioners measure and improve reliability, and how that idea increasingly overlaps with new technologies like the Internet of Things and artificial intelligence. As increasing dependence on increased reliability becomes evident in virtually every area of society and innovation, understanding the core elements and principles of this phenomenon is critical to ensuring both technological and societal advancement.

1.4 Faults Bearings

Bearings are a basic mechanical component that are required in numerous industrial applications to support and allow rotating machines to spin. The main purpose of these is to help the shafts or axles and prevent friction or the resistance of motion, which helps in the smooth working and proper rotation. They are not immune to wear and corrosion over time, even when taken care of, which can cause all sorts of problems that can affect the reliability and efficiency of machinery. Bearing failures are the most prevalent of these problems, often resulting in expensive unplanned downtime, impacted production, and, in some cases, even risking safety. In this introduction we will talk about why bearing failures are critical, the different types of failures, and how early detection and maintenance in an industrial setting is crucial. Bearings problems, however, can lead to excessive vibration, strange sounds, and higher friction, which can not only shorten a machine's life, but also lead to higher energy consumption. You need to identify & diagnose these issues if you want to minimize operational breakdowns before a catastrophic breakdown occurs. To assist companies, ensure their equipment maintains its reliability and efficiency, the types and causes of bearing defects will be thoroughly highlighted in the discussion that follows with the methods and resources used to monitor, detect, and repair these issues in real-time. Maintenance, reliability engineering and manufacturing professionals need to be very savvy on bearing failures in order to preserve equipment, maintain smooth operations and avoid production losses.

2 Literature Review

According to Li Liu et al. s work, one of the simplest and yet most difficult tasks in computer vision is to detect object instances in natural images for a wide range of categories [45]. Generic object recognition has seen a significant boom with the introduction of deep learning techniques which are capable of learning feature representations from data. In this tempestuous time of new heights, this work aims to offer a comprehensive survey of the recent progress of the area, which is due to deep learning methods. This survey reviews more than 300 academic papers covering aspects of generic object identification, including the detection framework, context modeling, object feature representation, training methods, evaluation metrics, and object proposal generation. We conclude the survey proposing some interesting directions for future work. The other, known as object detection, attempts to identify (typically unseen) occurrences of certain types of objects (e.g., individuals, vehicles, bikes, and pets) [1].

Xiaowei Huang et al. Deep neural networks (DNNs) are now able to reach human level performance on many popular activities, a remarkable progress in just a few years. As DNNs are used by a growing number of applications, particularly considering the well-known deadly accidents with autonomous cars, public concern has been raised as to the safety and reliability of DNNs. Having multiple publications

last few years definitely it shows that lots of study is being done to understand these issues and their solution. This survey reviews the existing research into improving the safety and dependability of DNNs across four separate areas: adversarial attack and defence, testing, interpretability, and verification. 202 papers, most published after 2017. It may well not be possible to cover all relevant research initiatives we aim to cover here all the past and ongoing research initiatives dedicated to ensuring the safety and reliability of DNNs. shows the exponential growth of the area with the number of surveyed papers for each calendar year from 2008 to 2018. Overall, we reviewed 202 publications [2].

The authors of this new paper work on improving the DNN inference accuracy, which they say is one of the most important performance metrics in the system, making it an integral issue. But in practice, it is often unknown since there are no ground truth labels and can differ considerably depending on real testing sets. This has caused huge worries about the reliability of DNNs, particularly in safety-critical applications. To solve this issue, we propose a blind solution for the reliability of DNNs that can track the actual inference accuracy on the user's dataset through a post-hoc processing. In particular, we present an accuracy monitor model based on neural nets that only takes the SoftMax probability outputs of the deployed DNN as input. Then, based on the above, this model estimates the true inference accuracy by predicting accuracy of DNN actual prediction result. The accuracy monitor model can be pre-trained on a dataset related to the target application of interest, making model transfer possible with only 1% of the user's dataset being passively labelled. For robustness in estimation, we further make use of a collection of monitor models obtained from Monte-Carlo dropout [3].

Upon deployment, an object detector in this system should perform at a level similar to that reported on its testing dataset, according to Quazi Marufu Rahman et al. However, when installed on mobile robots that operate in a range of challenging environmental conditions, the detector's efficacy may fluctuate and may suddenly decline. If ignored, this may lead to the robot acting in a hazardous and damaging way because of inaccurate and subpar item detections. In order to address this problem, we offer a cascaded neural network that tracks the object detector's performance by predicting the quality of the mean average precision (map) of the detector on a sliding window of the input frames. The proposed cascaded network makes use of the internal features of the deep neural network of the object detector. We evaluate our proposed approach for autonomous driving on several datasets and object detector combinations. Object detection is crucial for many applications in robotics and autonomous systems [4].

Quazi Marufu Rahman et al. state that safety-critical applications such as self-driving automobiles that operate in a range of difficult environmental conditions depend on this system's performance monitoring of object detection. Currently, object detectors are evaluated with summary metrics on a single dataset believed to be representative of all future deployment situations. This assumption is not accurate in practice, as performance varies according on deployment conditions. To address this issue, we offer an introspective approach to deployment performance monitoring that does not rely on ground truth data. We achieve this by predicting when the per-frame mean average precision drops below a critical threshold by taking advantage of the detector's intrinsic characteristics. We quantitatively evaluate and demonstrate our

method's ability to reduce risk by trading off making a poor decision by increasing the warning and evading discovery [5].

3 Existing System

The use of fuzzy convolutional neural networks based on the Internet of Things and fusion with multi-source sensing data for the classification and prediction of mechanical faults has become a new research hotspot. The current study adopts a fuzzy convolutional neural network-based method to mine and process fault signals from Case Western Reserve University (CWRU) bearing dataset. It also compares the accuracy of the proposed model with that of a model that uses a direct convolution neural network. The Fuzzification-based technique produced improved classification outcomes embedded in a connected layer. The average classification accuracy of the proposed method using fuzzy layer applied on bearing dataset is 99.87%. We compare the proposed method with other deep learning and machine-learning based approaches. The accuracy achieved using the proposed method outperformed its equals on all environments. The proposed technology is going to be used to identify mechanical motors problems and preventative recommendations.

4 Proposed System

We propose a non-feedback vibration emission system for data collecting from rotating apparatus, focused on bearing detection. In the preprocessing step (Fig 1), vibration signals can be denoised depending on the Hilbert transform. Then, a step from feature reduction, where PCA is computed based on preprocessing of features extraction and normalisation, is done in order to create a better analysis stage. The best features are selected using Sequential Floating Forward Selection (SFFS). In order to do this, after the feature extraction, Support Vector Machines (SVM) and Artificial Neural Networks (ANN) have been created that classify the different types of faults that can bear, learning thanks to an input of features that allows a quick and useful response. Coupled with a concise and fast fault localization approach increases the reliability of equipment during operation and ultimately saves time, man hours & financial wastage in equipment maintenance.

4.1 Load Bearing Fault Dataset

The dataset of load-bearing flaws, which probably include vibration data from rotating machinery under various loads and speeds. This dataset is crucial for training and assessing the resulting machine learning models. It most likely includes illustrations of many types of bearing faults, providing the algorithms with a large number of instances to work with. The success of the subsequent phases of the analysis depends on the calibre and variety of the dataset.

4.2 Feature Reduction Based on Normalisation and Feature Extraction Using PCA

To gain time on the analyses, this study features reduction using PCA. Principal Component Analysis (PCA) generates a new set of uncorrelated variables out of the original features using dimensionality reduction. The study based on PCA from feature extraction & normalisation aims to find and preserve the most important characteristics (features) of a dataset which can explain most of the variance in the

given data of interest. Normalisation Most probably means to normalise the Features Scales such that each one carries equal weight to the study.

4.3 SVM Classification Using SFFS Based on Feature Selection

The categorisation task involves the use of Support Vector Machines (SVM) to recognise and classify various bearing issues. The SVM technique was chosen because to its effectiveness in handling high-dimensional data and its ability to determine the most suitable hyperplanes for classification. The iterative feature selection technique known as Sequential Floating Forward Selection (SFFS) selects features based on how well they enhance classification performance. This stage is crucial for optimising the accuracy of the SVM model by retaining the most relevant bearing health characteristics.

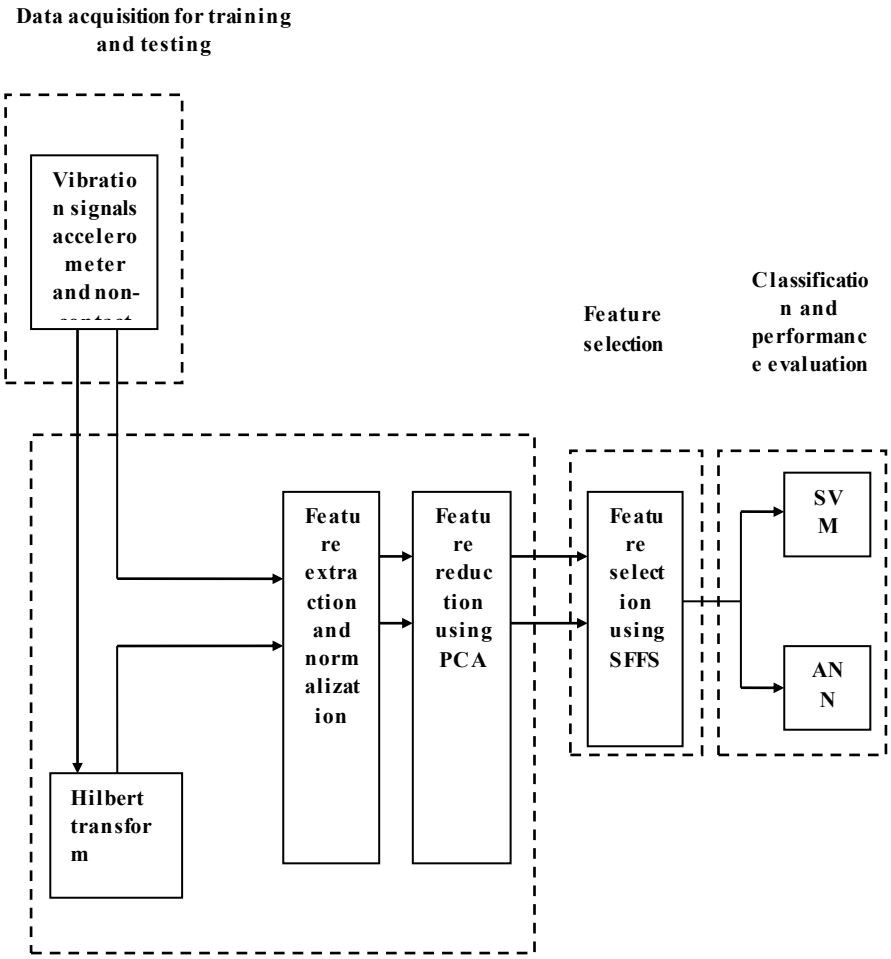

Fig.1. System Flow Diagram.

4.4 ANN Classification Using SFFS Based on Feature Selection

The study classifies bearing difficulties using both Support Vector Machines (SVM) and Artificial Neural Networks (ANN). The SVM approach heavily relies on Sequential Floating Forward Selection (SFFS) for feature selection. This iterative process facilitates the identification of the subset of characteristics that significantly enhances the classification performance of the ANN model. Based on the selected criteria, the study aims to increase the ANN's efficacy in identifying and classifying various bearing faults. The ability of neural networks to identify complex patterns in data is well known.

5 Result Analysis

The Result analysis describes how accurate approach is used in bearing defect identification and classification purpose. It was observed that the PCA feature reduction technique played an essential role in improving the output of subsequent classification procedures by preserving the most significant features. The two employed models, namely (SVM), and (ANN) were able to obtain good classification accuracy; however, use of Sequential Floating Floating selection (SFFS) feature selection strategy improved the performance of the both models significantly. By mitigating the overfitting effect through generalization, SFFS enhanced the performance of various models and reduced their computational complexity through filtering only most relevant features. Finally, the use of this multi planter techniquemost cost effective for defect detection indicates that it might be a new and successful assumption regarding the monitoring and maintenance of bearing health.

Table 1. Comparison Table.

Algorithm	Accuracy
EXISITNG SYSTEM	75
PROPOSED SYSTEM	82

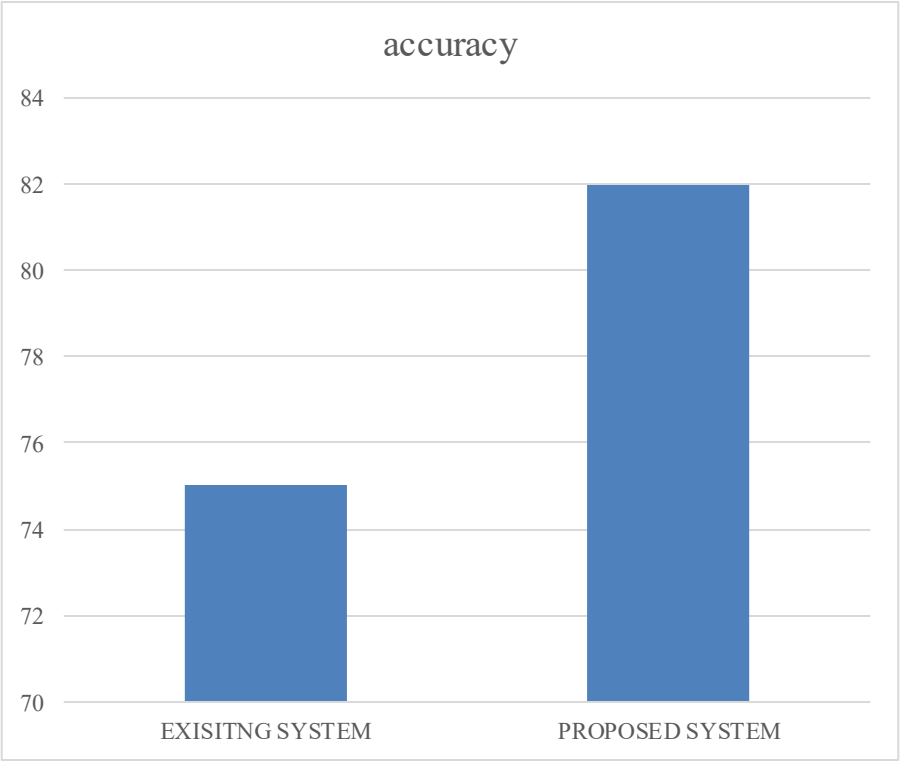

Fig. 2. Comparison Graph.

6 Conclusion

Overall, the study provides a robust and comprehensive approach for the evaluation and maintenance of bearing reliability. Using PCA based feature extraction and normalization, the method decreases the features in a large number of load-bearing fault databases, to enhance the effectiveness of the following studies. An SFFS feature selection and SVM and ANN classification establish a holistic approach for timely bearing failure detection. This can be done by carefully defining and classifying defects with the proposed solution essences level which can potentially save thousands in time and effort and response in equipment maintenance.

7 Future Work

By examining the use of more complex machine learning algorithms and including real-time monitoring capabilities, future research could expand the study's scope. Installing an online monitoring system allows for ongoing assessment of bearing health, facilitating more proactive maintenance schedules. Furthermore, the application of ensemble approaches or deep learning architectures may enhance the model's capacity to recognize intricate patterns in vibration data, thereby increasing the accuracy of defect identification. Additional investigation into the application of the proposed technique across different industrial settings and the consideration of changing environmental variables may help create a bearing health monitoring system that is both dependable and widely applicable.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

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