Advanced International Journal for Research

E-ISSN: XXXX-XXXX editor@aijfr.com

Volume 2, Issue 4, July – August 2024

Dynamic Observation of ML for Robotic Perception: A Survey of Recent Innovations

J. Bhaskar[1], Prof. L. M. Bharathi[2]

[1]Student, Department of Information Technology, Rajalakshmi Engineering College, Tamilnadu.
[2]Assistant Professor, Department of Information Technology, Rajalakshmi Engineering College, Tamilnadu.

Abstract

This project outlines the development and deployment of a non-contact vibration sensor designed to gather data from rotating machinery to facilitate early detection of bearing faults. The Hilbert transform is employed to reduce noise in the vibration signals, which are then processed using Principal Component Analysis (PCA) for dimensionality reduction and Sequential Floating Forward Selection (SFFS) for feature selection. Key features are utilized to identify and classify various bearing problems through Support Vector Machines (SVM) and Artificial Neural Network (ANN) algorithms. This approach offers a proactive and efficient solution for monitoring bearing health, emphasizing rapid fault detection and resulting in considerable savings in time, effort, and maintenance costs.

Keywords: machine learning, fault prediction, fuzzy convolution neural network (fcnn), heterogeneous sensing data fusion

1. Introduction

The advent of Internet of Things (IoT) technology has ushered in an era of enhanced connectivity, enabling diverse sensors to interact smoothly across various environments. However, the multitude of data sources in IoT systems adds complexity, especially in failure prediction contexts. To address the challenges posed by different data types and sources within the IoT framework, this study leverages fuzzy convolutional neural networks (FCNNs). By incorporating fuzzy logic, the FCNN model adeptly manages the uncertainties and imprecise information inherent in integrating data from multiple sensors. This research aims to enhance fault prediction accuracy in IoT environments, where traditional methods may fall short, by harnessing the capabilities of FCNNs.

Resilience and flexibility to analyses and learn from the combined data collected from many sensors.

1.1 Machine learning

Machine learning, a branch of artificial intelligence, has revolutionized how we address complex problems across various fields. This data-driven approach enables computers to learn and make predictions or decisions without explicit programming. Its transformative impact spans areas such as healthcare, finance, autonomous vehicles, and natural language processing. Utilizing algorithms and models, machine learning analyzes and identifies patterns in large datasets, delivering insights once deemed science fiction. As we navigate an era of vast data, machine learning has become crucial for interpreting complex information, often surpassing human abilities in tasks like image recognition, language translation, and game strategy. The growth of machine learning is driven by factors like the availability of extensive datasets, advances in computing power, and innovations in algorithm design.

1.2 Fault prediction

Fault prediction is a critical aspect of system reliability and performance enhancement that can revolutionize preventive maintenance strategies. By anticipating potential defects or anomalies before they escalate into significant issues, this predictive approach helps reduce downtime and prevent major failures. At its core, fault prediction leverages machine learning algorithms, advanced analytics, and historical data analysis to detect patterns and trends indicative of upcoming problems. Shifting from a reactive to a proactive approach, fault prediction is essential for ensuring the continuous and efficient operation of complex technological systems. This shift not only boosts system resilience but also significantly reduces operational costs and downtime.

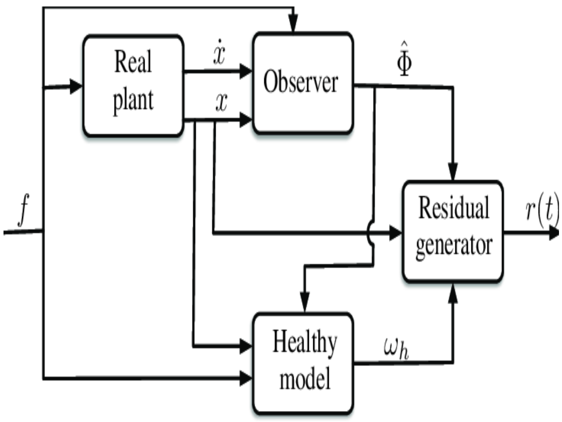


Figure 1. Fault prediction

1.3 Fuzzy convolution neural network (FCNNs)

A fuzzy convolutional neural network (FCNN) is a hybrid computational model that merges fuzzy logic with convolutional neural networks (CNNs). Fuzzy logic introduces the ability to handle uncertainty and imprecision by assigning degrees of truth to variables, providing a more nuanced, human-like reasoning process. Convolutional layers within CNNs excel at feature extraction, making them ideal for tasks such as image recognition. By combining these elements, FCNNs offer an effective approach to managing complex datasets with uncertain or imprecise information. This integration improves the network's capacity to analyze and learn from diverse data sources, making FCNNs particularly effective in applications where traditional neural networks might falter, such as in predicting and classifying varied and fuzzy sensor data in IoT settings

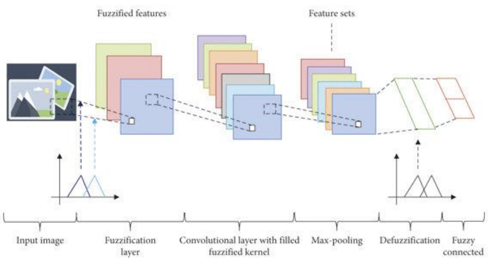


Figure 2. Fcnn

Advanced International Journal for Research

E-ISSN: XXXX-XXXX editor@aijfr.com

Volume 2, Issue 4, July – August 2024

1.4 Heterogeneous sensing data fusion

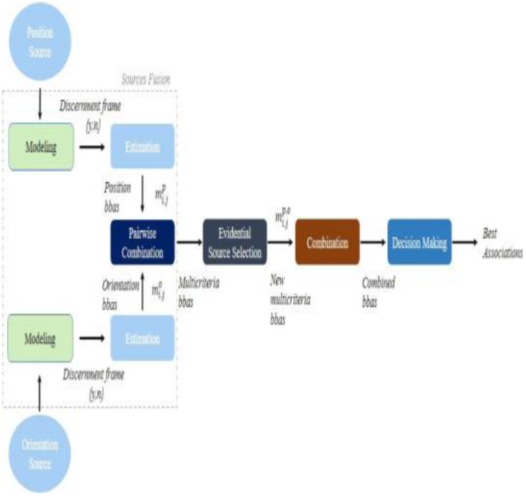


Figure 3. Heterogeneous sensing data fusion

Heterogeneous sensing data fusion is the process of combining and integrating data from various types of sensors to achieve a more comprehensive and accurate understanding of a given environment or system. This approach is crucial when multiple sensors, each with different modalities, resolutions, and principles, are used. The fusion process involves merging data from diverse sources such as image sensors, audio sensors, and heat sensors to create a unified and detailed representation. By leveraging the strengths of each sensor type while compensating for their limitations, this technique enhances the overall reliability and effectiveness of the data collected. Heterogeneous sensing data fusion is applicable in fields like surveillance, healthcare, and environmental monitoring, and is particularly valuable in complex settings like Internet of Things (IoT) environments, where a variety of sensors contribute to a thorough understanding of the system.

2. Literature survey

Connor et al. [1] have proposed that deep convolutional neural networks (CNNs) have achieved remarkable success in various computer vision tasks. However, these networks depend heavily on large datasets to prevent overfitting, which occurs when a model learns to perform exceedingly well on training data but fails to generalize to new data. Unfortunately, large datasets are not always available, particularly in fields like medical image analysis. This survey focuses on data augmentation as a solution to the problem of limited data. Data augmentation occupies methods that increase and improve training datasets to construct enhanced deep learning models. The survey covers numerous image augmentation approaches, including geometric transformations, color space augmentation, region filters, image blending, random erasing, feature space augmentation, adversarial training, generative adversarial networks, style transfer, and meta-learning.

Mateusz Buda et al. [2] examine the effect of class disparity on the execution of convolutional neural networks (CNNs) and assessed frequently used approaches to address this concern. While class disparity has been considerably studied in traditional machine learning, systematic research in the context of deep learning is inadequate. The study uses three standard datasets—MNIST, CIFAR-10, and ImageNet—to discover how discrepancy affects classification and compares various methods for modification, including oversampling.

M. Waqar Akram et al. [3] address the importance of defect detection in photovoltaic (PV) modules for improving system performance and reliability. They introduce an advanced outdoor infrared (IR) thermography method for identifying and analyzing defects in PV modules. Both functional and defective modules are tested under indoor and outdoor conditions. While indoor and outdoor measurements for functional modules are similar, defective modules show notable differences, with outdoor images often revealing fewer defects. The improved outdoor thermography method involves adjusting the temperature of PV modules by varying current conditions to create different temperature scenarios for better defect detection.

Xiaoxia Li et al. [4] propose that efficient condition monitoring and precise defect detection in large-scale photovoltaic (PV) farms require novel inspection methods and tools. This paper presents a deep learning-based solution using aerial images from unmanned aerial vehicles (UAVs) to recognize defect patterns in PV modules. The convolutional neural network (CNN) utilized in this approach categorizes various types of module defects, significantly enhancing the efficiency and accuracy of asset inspection and condition assessment in large PV farms.

R. Pierdicca et al. [5] highlight the increasing number of distributed photovoltaic (PV) plants and the associated challenges in monitoring and maintenance, which impact efficiency, reliability, safety, and stability. This paper introduces a novel approach using deep convolutional neural networks (DCNNs) to assess PV cell degradation. This study is unique in its use of thermal infrared data collected by drones, despite existing research on image classification. The experiments on the "photovoltaic images dataset" demonstrate the degradation issue and provide a thorough evaluation of the proposed method's effectiveness and suitability.

3. Exisiting system

As deep learning increasingly dominates computer vision tasks, it has become essential for robotic perception. However, this raises concerns about the reliability and safety of perception systems that depend on learning algorithms. Although there are established methods for certifying the safety and convergence of complex software systems during their design phase, the unpredictable nature of deployment environments and the complexity of learning-based perception pose challenges in applying these design-time verifications to run-time scenarios. Consequently, there is growing emphasis on monitoring the performance and reliability of perception systems during run-time, leading to the development of various approaches in the literature. This paper aims to explore these trends and provide an overview of the different strategies employed to tackle this issue.

4. Proposed system

The proposed system utilizes a non-contact vibration sensor to collect data from rotating machinery, enabling early detection of bearing failures. The Hilbert transform is applied to reduce noise in the vibration signals, and the data is subsequently analyzed with Principal Component Analysis (PCA) for dimensionality reduction and Sequential Floating Forward Selection (SFFS) for feature selection. Key features are then employed to detect and classify various bearing issues using Support Vector Machines (SVM) and Artificial Neural Networks (ANN). This comprehensive approach offers an effective and proactive method for monitoring and maintaining bearing health, focusing on rapid defect detection and resulting in considerable savings in time, effort, and maintenance costs.

4.1 Load-Bearing Fault Dataset

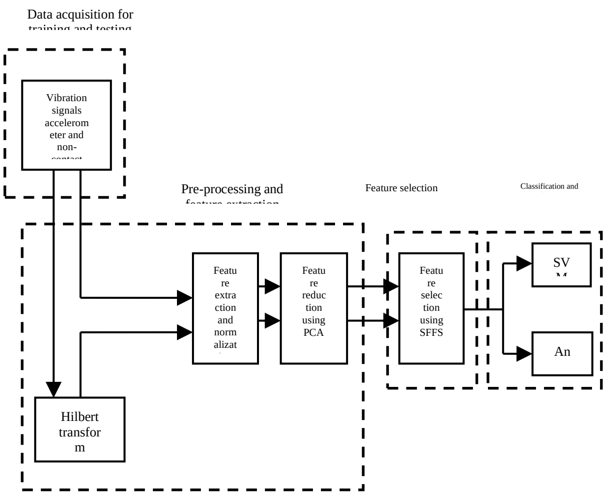
This module focuses on the collection and organization of a detailed dataset specifically for load-bearing issues in rotating machinery. It involves gathering vibration data under various loading conditions. This dataset forms the basis for subsequent analysis, ensuring that the system is trained and evaluated on a diverse range of load-induced bearing defects. The careful selection and assembly of this dataset are crucial for the system's accuracy and reliability in detecting and diagnosing faults associated with varying loads.

4.2 Feature Reduction Using PCA Based on Feature Extraction and Normalization

This module addresses the need for efficient feature extraction and normalization after acquiring the load-bearing fault dataset, utilizing Principal Component Analysis (PCA). PCA reduces the dataset's dimensionality while preserving essential information, which enhances computational efficiency and reduces the risk of overfitting. This step is vital for preparing the data for further analysis, ensuring that the most important features are retained, thereby improving the system's ability to accurately distinguish between different fault scenarios.

4.3 SVM Classification Based on Feature Selection Using SFFS

In this module, Support Vector Machines (SVM) are employed to classify faults accurately based on the processed data. Sequential Floating Forward Selection (SFFS) is used to refine feature selection by iteratively identifying and incorporating the most relevant features to boost the model's performance. This approach ensures that the SVM classifier is trained with the most pertinent data, enhancing its ability to detect and categorize load-bearing faults in the rotating machinery under analysis.



4.4 ANN Classification Based on Feature Selection Using SFFS

In this study, Artificial Neural Networks (ANNs) are employed alongside Support Vector Machines (SVMs) to classify bearing failures. Like with SVMs, Sequential Floating Forward Selection (SFFS) is used for feature selection in ANN models. This iterative process identifies a subset of features that significantly enhances the classification performance of the ANN model. ANNs are utilized for their ability to capture complex data patterns, which helps improve the ANN's effectiveness in identifying and categorizing various bearing issues based on the selected features.

Algorithm details

Support Vector Machines (SVMs) are a popular supervised machine learning technique used for classification and prediction tasks. Known for their accuracy in text classification and sentiment analysis, SVMs can train models to categorize data into predefined classes, such as positive and negative reviews. The SVM works by finding the optimal hyperplane that separates two classes and aims to maximize the margin between the closest data points of each class. The following code illustrates how to use SVM for classification:

```
From sklearn.svm import svc
# instantiate svm classifier
Svm_model = svc(kernel='linear', c=1.0)
# train the model
Svm_model.fit (x_train, y_train)
# make predictions
Svm_predictions = svm_model.predict(x_test)
```

Artificial Neural Networks (ANNs) are a category of machine learning models inspired by the structure and functioning of the human brain. An ANN consists of three types of layers: an input layer, one or more hidden layers, and an output layer, all composed of interconnected nodes. To make precise predictions, the network adjusts the weights of these connections during the training process.

```
From tensorflow.keras.models import sequential
From tensorflow.keras.layers import dense
# build ann model
Ann_model = sequential()
Ann_model.add(dense(units=128, activation='relu', input_dim=input_dim))
Ann_model.add(dense(units=1, activation='sigmoid'))
# compile the model
Ann_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
# train the model
Ann_model.fit(x_train, y_train, epochs=10, batch_size=32)
# make predictions
Ann_predictions = ann_model.predict (x_test)
```

5. Result analysis

Algorithm	Accuracy	Precision	Recall	F-measure
SVM	0.842	0.790	0.752	0.841
ANN	0.881	0.910	0.871	0.982

Table 1. Comparison table

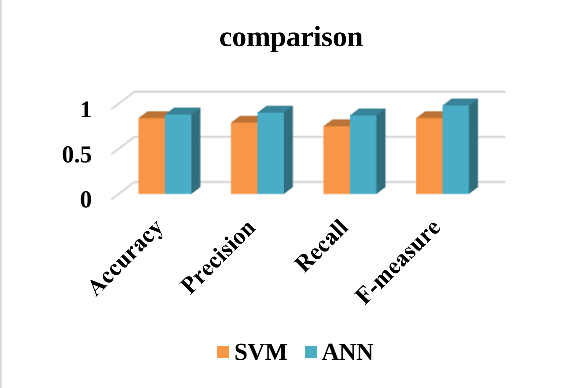


Figure 4. Comparison graph

The table summarizes the performance assessment results for the Support Vector Machine (SVM) and Artificial Neural Network (ANN) algorithms in the given task. The SVM algorithm achieves an overall accuracy of 84%, reflecting its effectiveness in correctly classifying samples. Its recall, which measures the algorithm's ability to identify all relevant instances, is 75%, and its precision, indicating the ability to avoid false positives, is 79%. The F-measure, which balances recall and precision, is 84%. In contrast, the ANN algorithm outperforms the SVM with an accuracy of 88%, demonstrating superior performance in correct classification. The ANN also shows strong precision at 90% and a recall rate of 87%, with a notably high F-measure of 98%, indicating a well-balanced performance between accuracy and recall. These metrics highlight the strengths of each algorithm and offer valuable insights into their effectiveness for the specific classification task.

6. Conclusion

The table summarizes the performance assessment results for the Support Vector Machine (SVM) and Artificial Neural Network (ANN) algorithms in the given task. The SVM algorithm achieves an overall accuracy of 84%, reflecting its effectiveness in correctly classifying samples. Its recall, which measures the algorithm's ability to identify all relevant instances, is 75%, and its precision, indicating the ability to avoid false positives, is 79%. The F-measure, which balances recall and precision, is 84%. In contrast, the ANN algorithm outperforms the SVM with an accuracy of 88%, demonstrating superior performance in correct classification. The ANN also shows strong precision at 90% and a recall rate of 87%, with a notably high F-measure of 98%, indicating a well-balanced performance between accuracy and recall. These metrics highlight the strengths of each algorithm and offer valuable insights into their effectiveness for the specific classification task.

7. Future work

Future efforts should focus on adapting and improving the proposed system to accommodate a broader array of industrial environments and types of machinery. Expanding research on the non-contact vibration sensor's adaptability to various operational conditions and environments will enhance the system's flexibility. Integrating real-time monitoring features and exploring the inclusion of emerging technologies such as edge computing or the Internet of Things (IoT) could provide a more dynamic and responsive method for monitoring bearing health. Ongoing research should aim at optimizing machine learning algorithms, with the potential addition of deep learning models to improve pattern recognition and fault detection.

References

1 "a survey on image data augmentation for deep learning," by c. Shorten and t. M. Khoshgoftaar, in j. Big data, vol. 6, no. January 1, 2019, art. No. 60, doi: 10.1186/s40537-019-0197-0.

2 "a systematic study of the class imbalance problem in convolutional neural networks," by m. Buda, a. Maki, and m. A. Mazurowski, neural networks, vol. 106, pp. Oct. 2018, pp. 249–259, doi: 10.1016/j.neunet.2018.07.011.

3 M. W. Akram, g. Li, y. Jin, x. Chen, c. Zhu, x. Zhao, m. Aleem, and a. Ahmad, "worked on outside thermography and handling of infrared pictures for deformity discovery in pv modules," sol. Energy, vol. 190, pp. 549-560, sep. 2019, doi: 10.1016/j.solener.2019.08.061.

4 "deep learning based module defect analysis for large-scale photovoltaic farms," ieee trans., x. Li, q. Yang, z. Lou, and w. Yan. Energy convers., vol. 34, no. 1, pp. Mar. 2019, 520–529, doi: 10.1109/tec.2018.2873358.

5 R. Pierdicca, e. S. Malinverni, f. Piccinini, m. Paolanti, a. Felicetti, and p. Zingaretti, "profound convolutional brain network for programmed location of harmed photovoltaic cells," int. Arch. Photogramm., remote sensing inf. Of space sci., vol. 42, pp. May 2018, pp. 893–900, doi: 10.5194/isprs archives-xlii-2-893-2018 is available.

6 "metadetect: uncertainty quantification and prediction quality estimates for object detection," by m. Schubert, k. Kahl, and m. Rottmann arxiv:2010.01695, 2020. [online]. [http://arxiv.org/abs/2010.01695] is accessible.

7 "iv-slam: introspective vision for simultaneous localization and mapping," by s. Rabiee and j. Biswas arxiv:2008.02760, 2020. Accessible over the internet at http://arxiv.org/abs/2008.02760

8 [p. Antonante, d. I. Spivak, and l. Carlone, "perception system monitoring and diagnosability," arxiv:2005.11816, 2020. Accessible over the internet at http://arxiv.org/abs/2005.11816

9 "automated evaluation of semantic segmentation robustness for autonomous driving," by w. Zhou, j. S. Berrio, s. Worrall, and e. Nebot ieee transactions on intell. Transp. Syst., vol. 21, no. 5, may 2020, pp. 1951–1963.

10 "online monitoring for neural network based monocular pedestrian pose estimation," by a. Gupta and l. Carlone arxiv:2005.05451 (2020). Accessible over the internet at http://arxiv.org/abs/2005.05451