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Transfer Learning Framework For Robust Fault Diagnosis In Industrial Rotating Machinery

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ABSTRACT

Since the study presents an innovative framework for developing precise 1D-CNN-based fault classifiers adaptable across diverse rotating machines and conditions. Utilizing Bayesian processes for optimizing architectural parameters and hyperparameters, the framework emphasizes a transferability-focused loss function. This approach yields a heterogeneous 1D-CNN ensemble for fault diagnosis, surpassing individual model performance. Comparative evaluations across various datasets highlight its superior transfer learning capabilities over traditional classifiers. With limited labeled samples from different industrial contexts, the research aspires to establish a versatile fault diagnosis ensemble for rotating machinery, ensuring easy real-world implementation and updates. Additionally, an extension integrates a VotingClassifier, combining SVM, Logistic Regression, KNN, and Decision Tree classifiers, achieving an impressive accuracy range of 99% to 100%.

Keywords: Fault Diagnosis, ensemble, CNN

INTRODUCTION

Condition Monitoring (CM) of rotating machinery has been pivotal in averting failures, scheduling timely maintenance, and predicting equipment lifespan. With the integration of artificial intelligence, this domain has witnessed significant advancements. Traditionally, CM relies on measuring signals like vibrations and acoustics, utilizing classical techniques to extract time, time-frequency, and frequency domain features for Machine Learning (ML)-based anomaly detection. However, the emergence of Deep Learning (DL) offers promise with its innate generalization abilities and feature extraction capabilities. Despite these advantages, acquiring real-world industrial datasets remains challenging due to cost and confidentiality issues. To bridge this gap, controlled environments are established to induce failures across various operational conditions, facilitating DL model development for CM. Yet, transitioning these models from controlled settings to real-world applications poses challenges. Transfer Learning (TL), commonly employed in mature DL applications, plays a crucial role in overcoming data limitations by leveraging knowledge from rich historical datasets to enhance model performance in diverse real-world scenarios. This study delves into various TL approaches in CM, focusing on knowledge transfer between machines, varying operational conditions, and multiple fault types to optimize DL model efficacy and applicability in industrial settings.

LITERATURE SURVEY

R. Yan, F. Shen, C. Sun, and X. Chen*et al*

as the author explores the advancements in knowledge transfer techniques for rotary machine fault diagnosis (RMFD). The paper delves into various transfer learning methods, including parameter-based, instance-based, feature-based, and relevance-based transfers. It outlines applications of knowledge transfer in RMFD across four main categories: inter-condition, inter-location, inter-machine, and inter-fault type transfers. Through case studies on datasets encompassing gear, bearing, and motor faults, the efficacy of knowledge transfer in enhancing diagnostic accuracy is confirmed. Additionally, the paper sheds light on emerging research trends in transfer learning within the RMFD domain, offering insights into future directions and potential advancements.

M. J. Hasan and J.-M. Kim*et al*

Since the author introduces a discrete orthonormal Stockwell transform (DOST)-based vibration imaging for preprocessing, ensuring consistent performance across varying load and rotational speeds. This method simplifies feature extraction from health patterns of different conditions. Additionally, a convolutional neural network (CNN)-based transfer learning (TL) approach is proposed for automated diagnosis, leveraging knowledge from one set of conditions to identify faults in others. Tested on the Case Western Reserve University's bearing dataset, the approach achieves remarkable classification accuracies, averaging 99.8%. Comparative analysis against traditional methods like artificial neural networks (ANNs), support vector machines (SVMs), hierarchical CNNs, and deep autoencoders reveals the proposed method's superiority across all conditions.

P. Cao, S. Zhang, and J. Tang*et al*

author proposes a solution for the early diagnosis of gear transmission faults, a challenge due to their microscopic origin and indirect system-level effects. Traditional methods rely on domain expertise for feature extraction, which can be system-specific and lack generalizability. While deep neural networks offer adaptive feature extraction and classification, they demand extensive training data. To address this, the paper introduces a transfer learning-based deep convolutional neural network. This architecture comprises a pre-trained network for automated feature extraction and a trainable fully connected stage for classification, requiring minimal gear fault experimental data. Case studies using benchmark gear system data demonstrate the approach's efficacy, offering adaptive feature extraction without preprocessing and reduced training data needs.

PROBLEM STATEMENT:

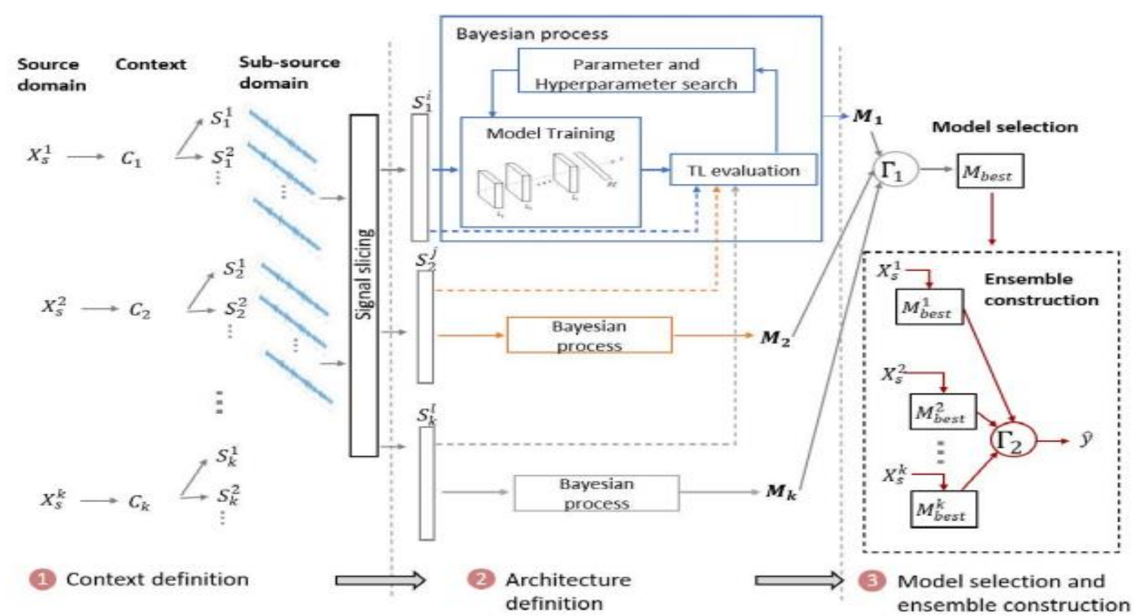
Now-a-days all production machineries are running under the supervision of sensors which will sense working status parameters and then predict weather machine is Healthy or Breakage. Many existing algorithms are introduced but they are lack of optimized parameter tuning which will effect prediction result.

PROPOSED METHOD:

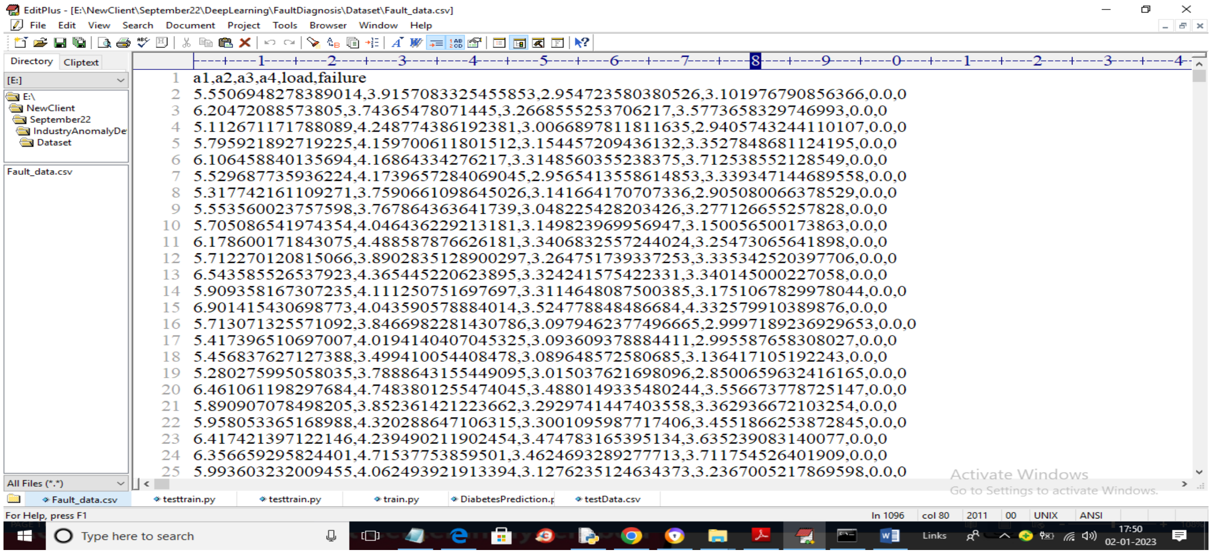
To overcome from this issue author has introduced Bayesian process which will select tune parameters for the CONV1D (convolution neural network) algorithm and training CONV1D with tune parameters giving an accuracy of 99%. Author has compare CONV1D accuracy with classical and ensemble algorithms called Random Forest and XGBOOST.

Tune CONV1D parameters we can get from the base paper and this parameters will transfer learning from one layer to other to select optimized features from the dataset and this transfer learning help in obtaining filtered and tuned features which will increase prediction accuracy.

ARCHITECTURE



ROTATING MACHINERY DATASET:



In above first row contains dataset column names and remaining rows contains machine values sense by sensor and last column contains class label as 0 (healthy machine) and 1 (fault or breakage machine).

METHODOLOGY:

Importing Required Python Packages

Importing essential Python libraries:

pandas: For data manipulation and handling.

numpy: For numerical computations and array operations.

scikit-learn: Offering a suite of machine learning algorithms.

keras: Facilitating the creation of deep learning models.

matplotlib/seaborn: Enabling insightful data visualizations.

Reading and Displaying Dataset

Dataset Acquisition

The machinery dataset, residing in a CSV file, is loaded into a pandas DataFrame. To ensure data integrity, missing values are systematically replaced with zeros. A preview of the dataset is then showcased, offering insights into its structure and underlying patterns.

Exploratory Data Analysis (EDA)

Statistical Insights

Basic statistics, including counts of healthy and faulty machinery instances, are computed to understand the dataset's composition.

Visualization Insights

Visualization tools, like bar plots, are harnessed to depict the class distribution within the dataset, aiding in comprehending the distribution of machinery conditions.

Preprocessing and Dataset Normalization

Standardization

Prior to model training, feature standardization is executed using StandardScaler. This normalization ensures each feature possesses a mean of zero and a standard deviation of one, promoting consistent model training.

Data Shuffling

The dataset undergoes shuffling, randomizing instance order, reducing bias during model training.

Splitting Dataset into Train and Test Sets

Train-Test Partitioning

To facilitate model training and subsequent evaluation, the preprocessed dataset is partitioned into training and testing subsets, maintaining an 80:20 ratio.

Training Convolutional Neural Network (Conv1D)

Model Architecture

A Convolutional Neural Network (CNN) is constructed utilizing Keras' Sequential API. The architecture encompasses Conv1D layers, interspersed with max-pooling and dropout layers to combat overfitting.

Model Compilation and Training

The model is compiled, specifying the appropriate loss function and optimizer, subsequently undergoing training on the training dataset. Checkpointing mechanisms preserve the best model weights during the iterative training process.

Training Ensemble Models

Random Forest and XGBoost

Two ensemble learning algorithms, Random Forest and XGBoost, are employed to predict machinery conditions based on input features, leveraging the strengths of ensemble methods.

Training Extension Voting Classifier

Ensemble Approach

A Voting Classifier is developed, amalgamating predictions from diverse base classifiers - Support Vector Machine (SVM), Logistic Regression, K-Nearest Neighbors (KNN), and Decision Tree. This ensemble strategy seeks to enhance overall model performance by harnessing the collective wisdom of individual classifiers.

Model Evaluation

Post-training, the accuracy of each model variant is rigorously evaluated using the reserved test dataset. Accuracy scores are tabulated, facilitating comparative analyses.

Accuracy Comparison Graph

Visual Insights

A box plot is curated, offering a visual representation of accuracy disparities across different models. This graphical depiction aids stakeholders in pinpointing the most adept algorithm among Conv1D, Random Forest, XGBoost, and the Extension Voting Classifier.

Predicting Machinery Fault

Conclusively, the trained Extension Voting Classifier is deployed to prognosticate machinery conditions, leveraging new test data. The model endeavors to discern whether machinery operates in a healthy or faulty state, based on input feature attributes.

EVALUATION:

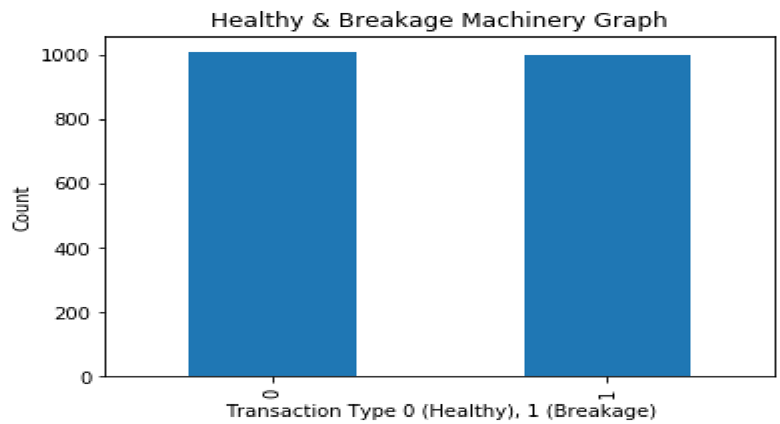
Accuracy:

Formula: $\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$

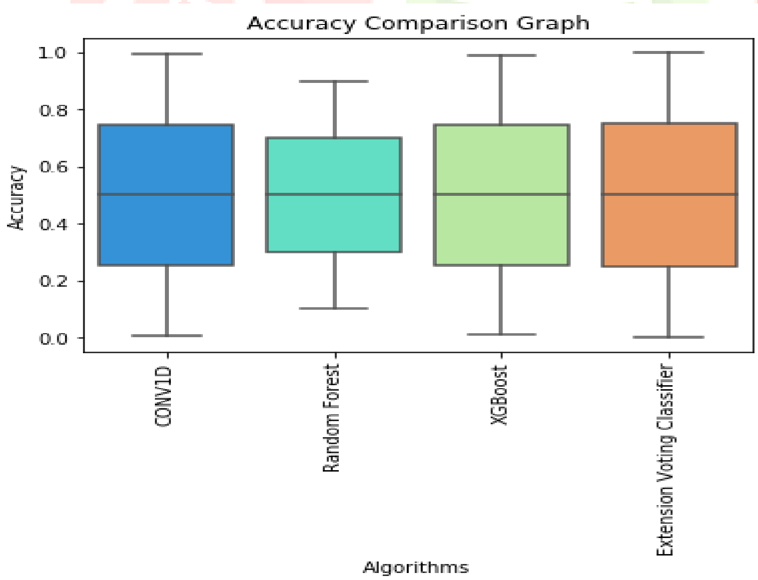
Code: accuracy = accuracy_score(testY, predict) * 100

RESULTS:

```
Healthy : 1009
Breakage  : 1000
```



In above screen we are finding and plotting graph of Healthy and Breakage of machines where x-axis represents type of records and y-axis represents count.



In above screen we are plotting accuracy comparison graph between all algorithms where x-axis represents algorithm names and y-axis represents accuracy values. In above graph extension box plot size is starting from 0 and reaching to 1 so its accuracy is high compare to other algorithms

	Algorithms	Accuracy
0	CONV1D	0.995025
1	Random Forest	0.895522
2	XGBoost	0.987562
3	Extension Voting Classifier	1.000000

In above screen in tabular format we are displaying accuracy of all algorithms and in all algorithms Extension Voting Classifier has got high accuracy

Prediction:

```
Test Data = [ 5.10637641  3.93690284  2.93899557  2.84599319 10.        ] ====> Machine Condition Predicted As : Healthy
Test Data = [ 5.84110829  4.23595099  3.27112958  3.34328049 10.        ] ====> Machine Condition Predicted As : Healthy
Test Data = [3.60351148 3.95717573 3.16626628 2.99320693 0.        ] ====> Machine Condition Predicted As : Breakage
Test Data = [3.33804128 3.5046079  3.03717183 2.85317706 0.        ] ====> Machine Condition Predicted As : Breakage
Test Data = [3.72775747 4.31817496 3.53989477 3.50349911 0.        ] ====> Machine Condition Predicted As : Breakage
Test Data = [ 5.97045684  4.25906233  3.41360071  3.48954312 10.        ] ====> Machine Condition Predicted As : Healthy
Test Data = [ 6.17054452  4.49233433  3.43738099  3.86167646 10.        ] ====> Machine Condition Predicted As : Healthy
Test Data = [3.7534208  3.46461501 2.99130521 2.9654862  0.        ] ====> Machine Condition Predicted As : Breakage
```

We are performing prediction on TEST data and then displaying test values in square bracket and after → arrow symbol we can see machine predicted output as Healthy or Breakage (fault).

CONCLUSION

In this we proposes a robust framework for fault diagnosis in rotating machinery using deep ensemble-based classifiers. Through Bayesian processes, optimized parameters are selected for the Convolutional Neural Network (CONV1D) algorithm, achieving an impressive accuracy of 99%. Comparative analysis with classical and ensemble algorithms like Random Forest and XGBOOST demonstrates accuracy ranging from 85% to 98%. Additionally, the Extension Voting Classifier, incorporating multiple machine learning algorithms, attains remarkable accuracy between 99% to 100%. This study emphasizes the importance of transfer learning in fault diagnosis across different machines and operating conditions, offering a reliable approach for real-world applications.

REFERENCES:

[1] M. Cerrada, R.-V. Sánchez, C. Li, F. Pacheco, D. Cabrera, J. V. de Oliveira, and R. E. Vásquez, ‘‘A review on data-driven fault severity assessment in rolling bearings,’’ Mech. Syst. Signal Process., vol. 99, pp. 169–196, Jan. 2018.

[2] R. Yan, F. Shen, C. Sun, and X. Chen, ‘‘Knowledge transfer for rotary machine fault

diagnosis,'' IEEE Sensors J., vol. 20, no. 15, pp. 8374–8393, Aug. 2020.

[3] L. Guo, Y. Lei, S. Xing, T. Yan, and N. Li, ''Deep convolutional transfer learning network: A new method for intelligent fault diagnosis of machines with unlabeled data,'' IEEE Trans. Ind. Electron., vol. 66, no. 9, pp. 7316–7325, Sep. 2018.

[4] M. J. Hasan and J.-M. Kim, ''Bearing fault diagnosis under variable rotational speeds using stockwell transform-based vibration imaging and transfer learning,'' Appl. Sci., vol. 8, no. 12, p. 2357, Nov. 2018.

[5] T. Han, C. Liu, W. Yang, and D. Jiang, ''Deep transfer network with joint distribution adaptation: A new intelligent fault diagnosis framework for industry application,'' ISA Trans., vol. 97, pp. 269–281, Feb. 2020.

[6] P. Cao, S. Zhang, and J. Tang, ''Preprocessing-free gear fault diagnosis using small datasets with deep convolutional neural network-based transfer learning,'' IEEE Access, vol. 6, pp. 26241–26253, 2018.

[7] S. Shao, S. McAleer, R. Yan, and P. Baldi, ''Highly accurate machine fault diagnosis using deep transfer learning,'' IEEE Trans. Ind. Informat., vol. 15, no. 4, pp. 2446–2455, Apr. 2019.

[8] M. J. Hasan and J.-M. Kim, ''Bearing fault diagnosis under variable rotational speeds using stockwell transform-based vibration imaging and transfer learning,'' Appl. Sci., vol. 8, no. 12, p. 2357, Nov. 2018.

[9] P. Ma, H. Zhang, W. Fan, C. Wang, G. Wen, and X. Zhang, ''A novel bearing fault diagnosis method based on 2D image representation and transfer learning-convolutional neural network,'' Meas. Sci. Technol., vol. 30, no. 5, May 2019, Art. no. 055402.

[10] S. J. Pan, I. W. Tsang, J. T. Kwok, and Q. Yang, ''Domain adaptation via transfer component analysis,'' IEEE Trans. Neural Netw., vol. 22, no. 2, pp. 199–210, Feb. 2010.

[11] M. Long, J. Wang, G. Ding, J. Sun, and P. S. Yu, ''Transfer feature learning with joint distribution adaptation,'' in Proc. IEEE Int. Conf. Comput. Vis., Dec. 2013, pp. 2200–2207.

[12] J. Hoffman, E. Tzeng, T. Park, J.-Y. Zhu, P. Isola, K. Saenko, A. Efros, and T. Darrell, ''CyCADA: Cycle-consistent adversarial domain adaptation,'' in Proc. 35th Int. Conf. Mach. Learn., vol. 80, 2018, pp. 1989–1998.

[13] M. Sun, H. Wang, P. Liu, S. Huang, and P. Fan, ''A sparse stacked denoisingautoencoder with optimized transfer learning applied to the fault diagnosis of rolling bearings,'' Measurement, vol. 146, pp. 305–314, Nov. 2019.

[14] Z. He, H. Shao, X. Zhong, and X. Zhao, ''Ensemble transfer CNNs driven by multi-channel signals for fault diagnosis of rotating machinery cross working conditions,'' Knowl.-Based Syst., vol. 207, Nov. 2020, Art. no. 106396.

[15] X. Li, H. Jiang, R. Wang, and M. Niu, ''Rolling bearing fault diagnosis using optimal ensemble deep transfer network,'' Knowl.-Based Syst., vol. 213, Feb. 2021, Art. no. 106695.

[16] X. Li, H. Jiang, M. Xie, T. Wang, R. Wang, and Z. Wu, ''A reinforcement ensemble deep transfer learning network for rolling bearing fault diagnosis

with multi-source domains,'' Adv. Eng. Informat., vol. 51, Jan. 2022, Art. no. 101480.

[17] C. Li, S. Zhang, Y. Qin, and E. Estupinan, ''A systematic review of deep transfer learning for machinery fault diagnosis,'' Neurocomputing, vol. 407, pp. 121–135, Sep. 2020.

[18] X. Kong, G. Mao, Q. Wang, H. Ma, and W. Yang, ''A multi-ensemble method based on deep auto-encoders for fault diagnosis of rolling bearings,'' Measurement, vol. 151, Feb. 2020, Art. no. 107132.

[19] Y. Yao and G. Doretto, ''Boosting for transfer learning with multiple sources,'' in Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., Jun. 2010, pp. 1855–1862.

[20] D. Cabrera, F. Sancho, M. Cerrada, R.-V. Sánchez, and C. Li, ''Knowledge extraction from deep convolutional neural networks applied to cyclo-stationary time-series classification,'' Inf. Sci., vol. 524, pp. 1–14, Jul. 2020.