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RESEARCH

Online Gear Wear Particle Detection and Categorization Using a Convolutional Neural Network Algorithm Integrated with Cascade Classifier

Kunal Kumar Gupta[a], Harish Hirani[b], S. M. Muzakkir[c,*]

[a]*Nagarjuna College of Engineering and Technology, Bangalore, India,*
[b]*Department of Mechanical Engineering, Indian Institute of Technology Delhi, India,*
[c]*Department of Mechanical Engineering, Jamia Millia Islamia, New Delhi, India.*

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* Corresponding author:

S. M. Muzakkir
E-mail: smmuzakkir@jmi.ac.in

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A B S T R A C T

Most gears fail because of wear caused by rubbing, metal to metal contact, contamination, or breakdown of lubrication. Because of this, figuring out how to find and sort wear debris particles is an important area of research for both predictive and proactive maintenance. By putting these wear particles into different categories like spherical, cutting, fatigue, sliding and rubbing, it would be possible to identify the wear modes present in the gearbox and predict the nature of failure and condition of the system. The present research aims to automate the detection and classification process using the Convolutional Neural Network (CNN) integrated with Cascade classifier. CNN automatically extracts different suitable features from images by applying multiple filters on it and also reduces the complexity of image processing whereas the Cascade classifier is used to detect the particles by differentiating between positive and negative images by applying the Haar-like features into it. The objective of the research work is to provide a most efficient and accurate detection and classification of wear debris particles using a trained cascade classifier integrated with a customized lightweight CNN model named as Wear Particle Classifier Net (WPCnet).

1. INTRODUCTION

It is crucial to have an early warning system for any gearbox faults so that appropriate action can be taken to avoid a disastrous failure. This would make it possible to calculate the usable remaining life and make planning maintenance strategies easier. The faults in the gearbox are generally manifested in the form of wear of gears and show up as wear particles in the lubricant. The tiny particles produced by the metal-to-metal interaction between the two gears are known as wear debris. Many significant pieces of information about the machine in operation can be gleaned from these particles with the right research. The classification of the wear debris can be used to determine the level of wear and the wear process.

Once the data has been extracted from the wear debris, it can be used to specify the machine's state. However, it's crucial to classify this debris because different particle sizes, shapes, and other characteristics correlate to various wear mechanisms, which correspond to various faults. Six different kinds of metallic wear debris were categorized by Peng et al. [1] using a theory of grey relational grades, and the weighting factors were determined using fuzzy logic. This research has shown that wear particles can be successfully classified using a grey system and fuzzy logic. In his review of several research articles, Raadnui [2] emphasized the importance of enhancing the availability of "intelligent" objective methods for carrying out wear particle analysis. To increase the precision and speed of wear particle identification, Wang et al. [3] suggested a novel algorithm that combines principal component analysis and grey relational analysis. Using the particle boundary signal to examine wear particle features is the primary component of Yuan et al.'s new radial concave deviation (RCD) technique, which was described in their paper [4]. To identify four different kinds of wear debris, including cutting, sphere, fatigue, and severe sliding particles, Peng et al. [5] suggested a hybrid convolution neural network that would be used in conjunction with transfer learning (TL) and support vector machines (SVM). When wear particles stick together and conventional methods of wear debris identification are unable to classify wear particles, Peng et al. [6] proposed a way of classifying wear debris. Liu et al [7] proposed a CNN model named DWear to semantically segment fatigue, severe sliding particles and four other types of particles, namely, chain, spherical, cutting and oxide particles, which unifies segmentation and recognition together especially when the fatigue and severe sliding wear particle are similar in morphology while different in wear mechanism. In order to obtain smooth foreground object contours while dealing with noise, varying lighting, and dynamic backgrounds, Reddy et al. [8] suggested a block-based approach. Identification of wear particles can benefit greatly from this. The color shift visible to the naked eye relies on the concentration of CN-, and Bej et al. [9] developed a chemo-sensor for the detection of CN- from aqueous phase with a permissible level detection limit. Laghari et al [10] proposed a knowledge-based system for analysis of microscopic wear particles in order to classify these particles according to their morphological attributes of size, shape, edge detail, thickness ratio, color, and texture, and by using this classification thereby predict wear failure modes in engines and other machinery. A method to identify morphological characteristics that categorize wear particles in relation to the wear process from which they originate and allow the automatic identification without human expertise was suggested by Gonçalves et al. [11]. The approach is founded on the analysis of varieties of microscopic wear particles using Multi-Layer Perceptron (MLP). Through the classification of the particles based on machine learning, Jur'anek et al. [12] presented a new approach to wear debris analysis. The suggested classification method is based on supervised machine learning and the visual resemblance of the particles. A quick to use method for journal bearing design was described by Hirani et al. in their article [13]. Without requiring a human specialist, Liu et al.'s [14] suggested for a pattern recognition system for wear particle analysis. An unsupervised segmentation algorithm based on a local color-texture feature is used to automatically divide the images. Sengupta et al. [15] and Goilkar et al. [16] demonstrated that a protective layer on a mild steel component will lessen corrosion, avoid material wear, and keep outside particles from getting into the lubricant. UstbNet is a better lightweight convolutional neural network that Wang et al [17] suggested for the classification of wear debris images.

To hasten model convergence and raise classification accuracy, several techniques were used, including data augmentation, batch normalization, number and size modification of convolution kernels, and loss function optimization. A new digital CNN (Cellular Neural Network) architecture for pattern recognition was introduced by Raschman et al. in their study [18]. The chip's area consumption and the computation speed per iteration were the two key design factors. Following a thorough analysis of existing methods, Qi et al. [19] introduced two unique network architectures for volumetric CNNs to enhance both volumetric CNNs and multi-view CNNs. By incorporating recurrent connections into each convolutional layer, Liang et al. [20] suggested a recurrent CNN (RCNN) for object recognition. Geng et al [21] surveyed the powerful CNNs and novel elaborate layers, structures and strategies, especially including those that have achieved the state-of-the-art results on the Pascal VOC 2012 semantic segmentation challenge and proposed several possible directions and approaches to incorporate existing effective methods as components to enhance CNNs for the segmentation of specific semantic objects. Radenovi et al. [22] suggested to completely automate the process of optimizing CNNs for image retrieval on a large collection of unordered images. In their novel two-stream CNN design for semantic segmentation, Takikawa et al. [23] suggested explicitly wiring shape information as a distinct processing branch, or shape stream, that processes data concurrently with the traditional stream. In order to progress CNN technology, Khan et al. [24] investigated a number of concepts, including the use of various activation and loss functions, parameter optimization, regularization, and architectural innovations. The recent innovations in CNN architectures were categorized into seven distinct categories after the intrinsic taxonomy contained in the recently reported deep CNN architectures was examined. To provide a clear grasp of the hyper-parameter tuning of those models, Sultana et al. [25] reviewed the development of both semantic and instance segmentation work based on CNN, specified comparative architectural details of some state-of-the-art models, and discussed their training details.

Ahmed at al [26] considered different sizes and numbers of filters with CNN to determine their effect on accuracy of classification. Azad et al [27] proposed a novel architecture that integrates a set of Difference of Gaussians (DoG) to attenuate high-frequency local components in the feature space to remove the texture bias in the context of few-shot learning thereby producing a set of modified feature maps, whose high-frequency components are diminished at different standard deviation values of the Gaussian distribution in the spatial domain. To extract debris and bubble images using the Otsu method, Wang et al. [28] suggested a motion object extraction algorithm based on background differences. A convolutional neural network (CNN) algorithm is then used to differentiate between bubbles and debris. Jia et al. [29] showed that for intelligent wear particle classification, deep convolutional neural networks best suit using transfer learning and achieve an accuracy level of 88.39% but the missing part in their paper is the detection of the particles which was envisaged as the future work, but this model is included in the proposed integrated model WPCNet. CNN is the best fit for online analysis, which is used in the present paper.

Wu et al. [30] showed multi-scale condition and corrosion expansion method and watershed segmentation method to separate the particle in the particle chain. To create a fault-prediction model using a machine learning approach, Poddar et al. [31] studied the acoustic emission signals that emerged from journal bearings in both their normal operating conditions and their faulty states, specifically cavitation, particle contamination, and oil starvation. To predict outputs like Form Factor, Convexity, Aspect Ratio, Solidity, and Roundness with respect to Running Hour, Engine RPM, and Engine Oil temperature, Mohanty et al. [32] studied the morphological characteristics of wear particles and proposed an intelligence-based ANN model using feed-forward backpropagation. To improve the efficiency of wear classification for all five categories, Wang et al. [33] proposed an integrated model of BP neural network and CNN algorithm; however, due to the lack of training data, accuracy was kept low for the sliding and fatigue particles, which is resolved by the proposed WPCNet model.

Thomas, et al. [34] relied on computer image analysis techniques to extract the morphological features of particles from the images and then classify the particles manually based on the extracted features, which lacks automation in the wear particle classification process. The proposed method, however, overcomes this limitation by automating the classification using CNN. Stachowiak et al. [35] proposed wear particle classification based on particle shape and its surface texture and used SEM technology to capture the particle image and to create the dataset for classification and automate the classification process using linear SVM which is a machine learning based approach which is improved by the proposed method in this paper by using CNN algorithm which automatically extracts the feature from the images. Peng et al. investigated the correlation between vibration analysis and wear debris analysis and identified the dependent and independent roles of vibration and wear debris analyses in predicting and diagnosing machine faults, which inspired us to automate the process of wear debris analysis to diagnose machine faults [36].

Hu et al. [37] demonstrated that a vibration indicator can be utilized to evaluate the effects of wear on gear performance. The authors have extracted a gear state vector from time synchronous averaged gear signals to describe the gear state. Wang et al. [38] demonstrated that two sets of Haar-like features, the original Haar-like features and the extended Haar-like features, can be used for extended cascading classifiers to detect cracks via stage classifiers. Haar-like features were used to depict fracture regions and train a cascading classifier for detecting cracks in wind turbine blades. This information is then integrated with the cascading classifier to detect and classify gear wear particles. Peng et al. [39] have shown an enhanced version of automatic wear particle detection and classification process using a cascade of two convolutional neural networks and a support vector machine (SVM) classifier reduces the computation expense and improves the accuracy but the classification of rubbing particle has not been attempted and the accuracy is low. Liu et al. [40] proposed a CNN model that is able to semantically segment fatigue, severe sliding particles and four other types of particles: chain, spherical, cutting and oxide particles and this knowledge can be further utilize to enhance the WPCNet model for the particle segmentation in online wear particle classification. Liu et al. [7] proposed a deep convolutional neural network (DCNN) with three modules and have used handcrafted features to classify the wear particle but it is only limited to two classes that are fatigue and sliding which is overcome by proposed WPCNet by including five classes of classification including rubbing, cutting and spherical. For end-to-end processing, the DCNN can automatically learn features through a layer-wise representation and achieve semantic segmentation of distinct wear particles in ferro-graph images.

The increase in operating conditions/temperature may increase the formation of wear particles [41]. Improper assembly of gear pairs can result in misalignment, which can be a significant factor in the formation of wear particles [42]. To understand the effect of various condition just usage of online condition monitoring may not be sufficient and to its widespread usage ML methods [43] now are required. Ciaburro et al [44] proposed a new methodology for automating the fan maintenance procedures based on the recording of the acoustic emission. The failure diagnosis using deep learning was evaluated for the detection of dust deposits on the blades of an axial fan.

The main aim of this research work is to automate the complete process of detection and classification of wear particles in efficient manner. As compared to the conventional methods of detection and classification of wear particles, where the wear particle image collection is carried out in offline mode using SEM technology, the online automatic detection and classification of wear particles is the present need. Some of the images of wear particles obtained using SEM are shown in Figure 1.

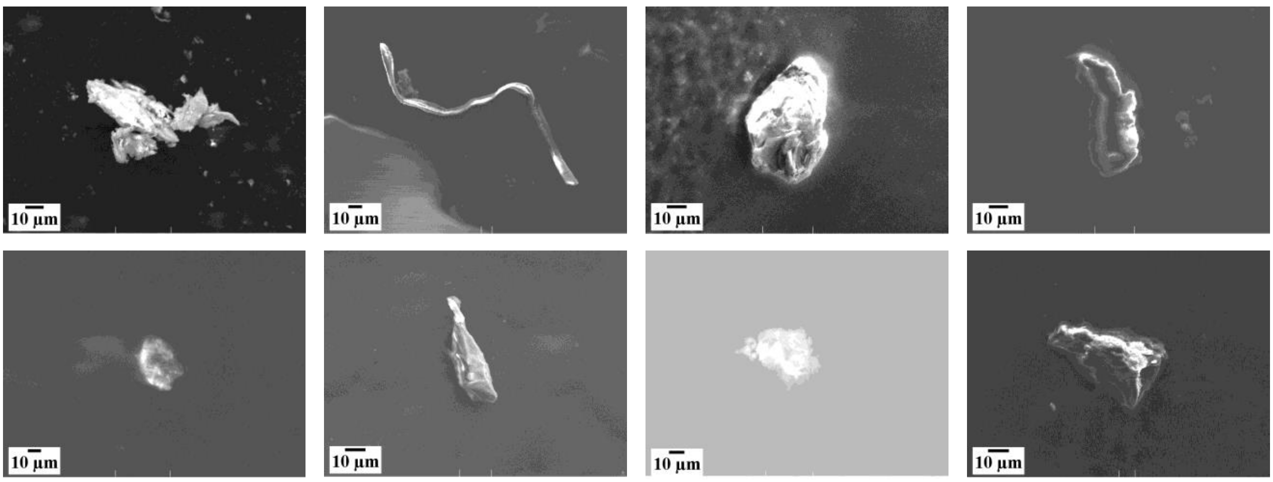


Fig. 1. SEM images of wear particles.

The use of SEM technology is an offline activity which is not only costly but also time consuming. Moreover, expert operator is required to capture the images. After images collection, the analysis of the images requires expert knowledge to derive the morphological features. To avoid all these conventional methods which is dependent on human skills, a new method to automate the complete process is presented in this research work.

The proposed research work presents a method for highly accurate detection and classification of wear particles that can be adopted by various industrial units for real-time, ongoing monitoring of gear tools. This objective is achieved by integrating the cascade classifier with the light weight WPCNet CNN model for the wear particle classification. The WPCNet CNN model and cascade classifier are combined in the current research work to present a novel method to automate the detection and classification of wear particles. This technique, after only 100 epochs, was able to reach the highest accuracy of 97.4%. This shows that, when compared to all other conventional techniques, it is the most effective technique for the detection and classification of wear particles.

The article is structured as follows: In Section 2, the methodology of wear particle classification is described in detail, followed by the experimental details in Section 3. The wear particle classification which includes the data pre-processing, training of the model and prediction are mentioned in Section 4, while Section 5 presents the results of the experimental studies and the corresponding discussion. Finally, the article concludes with key findings in Section 6.

2. METHODOLOGY

The main aim is to achieve the most accurate and efficient detection and classification of gear wear particles. In order to achieve this objective, the trained cascade classifier is integrated with the WPCNet CNN model. The complete process can be divided into two stages: in the first stage WPCNet CNN model is defined and trained for the wear debris classification and in the second stage CNN model is integrated with trained cascade classifier to detect the particle and classify it into five different classes that is Rubbing, Cutting, Spherical, Fatigue and Severe sliding. The architecture of the WPCNet CNN model is depicted in Figure 2.

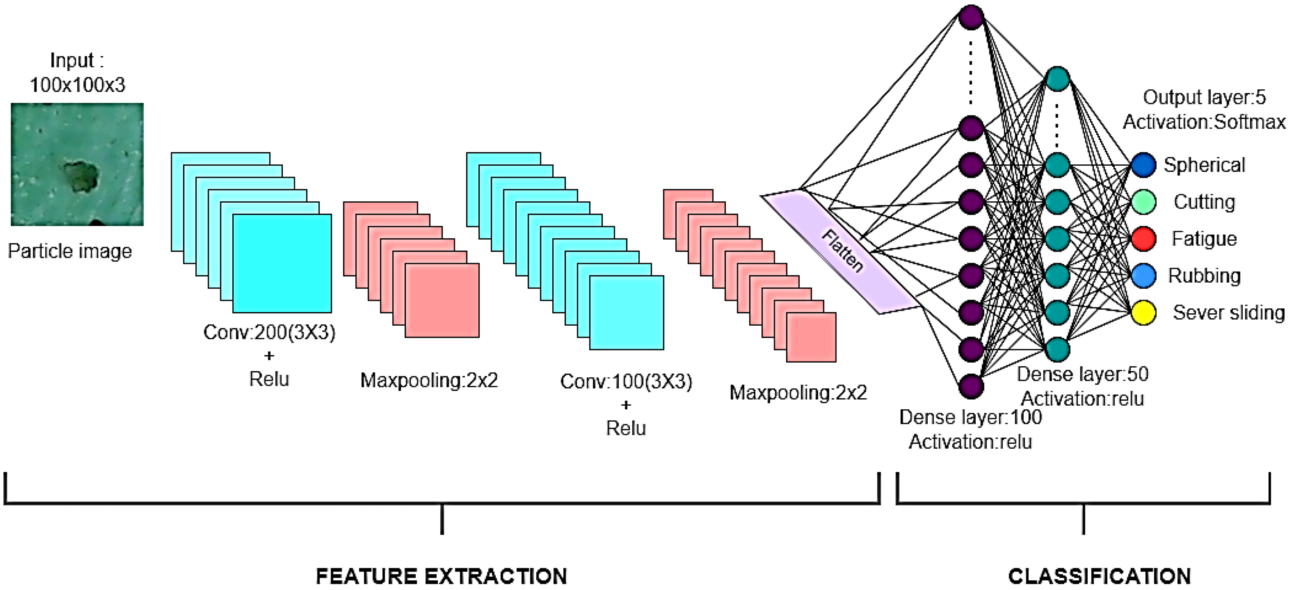


Fig. 2. Convolutional neural network WBCNet.

In each convolutional layer, the kernel size and kernel number and number of neurons in fully connected layer are given in Table 1.

As provided in Table 1, the architecture of the WPCNet CNN model consists of two convolutions layers of size 3x3 with 200 and 100 filters respectively. The activation function used with convolutions layers are ReLU and the filters are used to extract multiple features from the input images. Maximum pooling layer with pool size 2x2 is used to extract the maximum features from the feature map generated from the convolution layer. To convert the 2-Dimensional matrix to 1-Dimensional array, a Flatten layer is added so that the 1-d array value is provided to the fully connected layers for the classification purpose. Before sending to fully connected layers Dropout layer is added with value 0.5 to reduce the value 50% randomly and sent to the first fully connected layer with 100 nodes and then to the fully connected layer with 50 nodes. The activation function used with both the hidden layer is ReLU and Softmax activation function is used with the output layer of five nodes for the five classes of classification i.e., Cutting, Rubbing, Sliding, Fatigue and Spherical. Adam is used as an optimizer for the optimization of learning process with the learning rate value of 0.001 and Categorical crossentropy is used as loss function to reduce the error in learning process which subsequently helps in acquiring high classification accuracy. The complete model will be able to identify and classify the wear debris particle in real time effectively by integrating the WPCNet CNN model with Cascade classifier. The integration of both models was accomplished using the Juypter Notebook, a popular Python tool. The trained WPCNet CNN model is first called, and after particle detection is complete, the Cascade classifier uses it for classification. The Cascade classifier in the complete model allows the model to identify the particle, whereas the CNN model allows the model to classify the detected particle. Integration is necessary for the process to occur concurrently.

Table 1. WPCNet network parameters.

Model Content	**Details**
First convolution layer	200 filters, size 3x3, ReLU, input 100x100
Max pooling layer	Pooling size 2X2
Second convolution layer	100 filters, size 3x3, ReLU
Max pooling layer	Pooling size 2x2
Flatten layer	Convert 2D matrix into 1D vector
Dropout	0.5 (Dropout 50% randomly)
First dense layer	100 Nodes, ReLU
Second dense layer	50 Nodes, ReLU
Output layer	5 Nodes for 5 classes, Softmax
Loss function	Categorical cross_entropy
Learning rate	0.001
Optimizer	Adam

A flow-chart of the methodology is given in Figure 3.

3. EXPERIMENTAL DETAILS

The experimental test rig is shown in Figure 4 (a) and 4 (b). A single stage gearbox with straight tooth gears (involute tooth profile with standard pressure angle of 20°) having a speed ratio of 2:1 is used (27 teeth on pinion and 53 teeth on gear). The module of gear teeth is 2 mm. The face width of gear pair is 33 mm. The pitch diameter of pinion is 54 mm and that of gear is 106 mm. The base diameter is 50.7 mm and 99.6 mm respectively for the pinion and gear. The gear material is EN19. The lubricant used is GL-5 80W-90, the splash lubrication system is used. The gear box is coupled to a 30 kW DC electric motor through L-type standard jaw couplings. eddy current dynamometer, online condition monitoring sensors, and a PC for data storage. The loading on the gearbox is provided by the attached dynamometer E-50 (eddy current type). The description of the experimental setup is also given in [43] and [45].

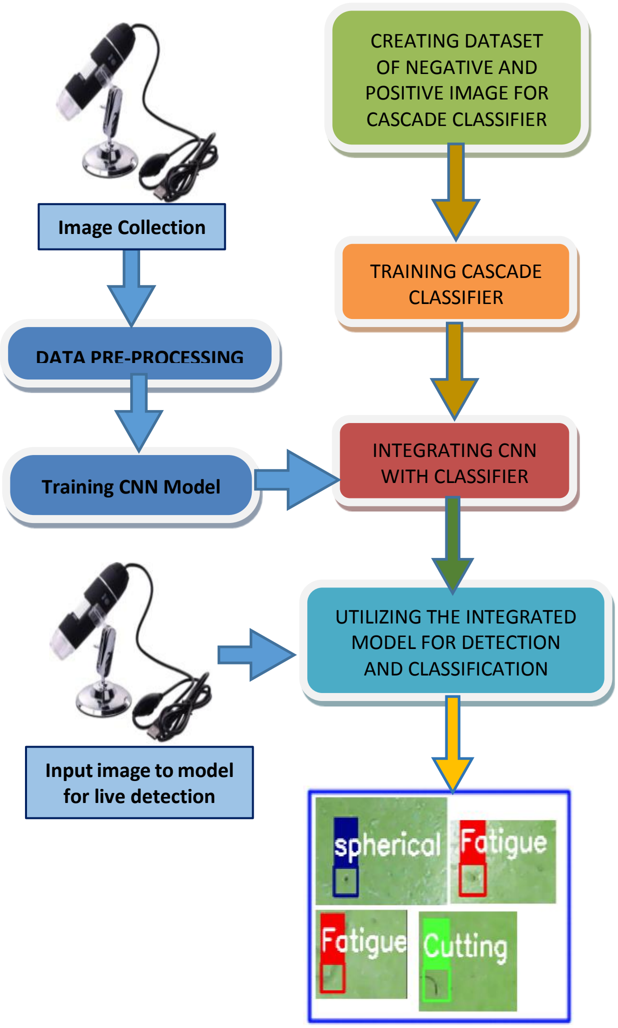
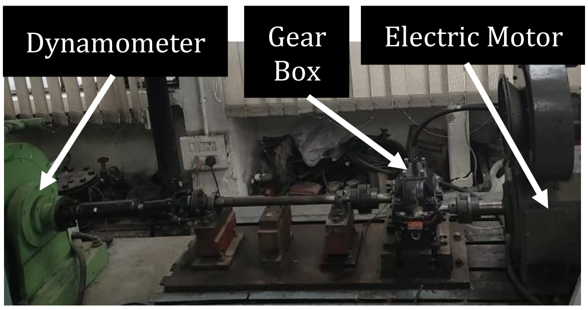
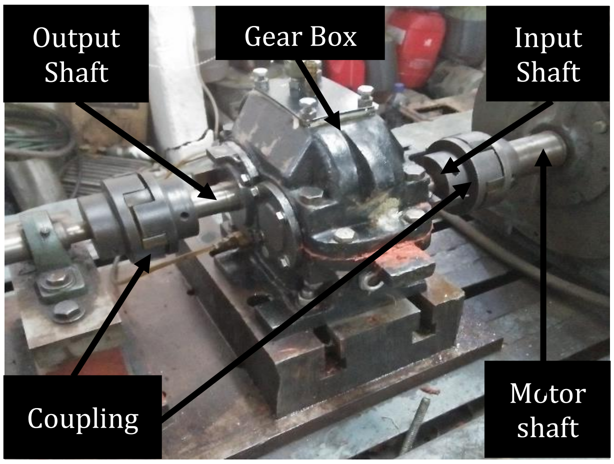


Fig. 3. Flow-chart of the methodology.



(a) Experimental Setup



(b) Closeup view of Gearbox

Fig. 4. Experimental setup.

A digital microscope camera with an 800x zoom was used to capture the particle picture. The digital camera is directly connected to the computer via a USB port, and using the command line "source1=cv2.VideoCapture(1)", it transmits live images to the Python-based Juypter Notebook platform.

This would guarantee that all calculations on the gathered live images take place in a single location. Below is some additional information about the microscopic camera: 5X to 800X magnification ratio, Dual focus optical system, Snapshot 4X digital zoom, HD 720P camera, 4-1/2" (115mm) focusing distance, 4X sequence mode, digital zoom USB 2.0 and USB 1.1 suitable interface Dimensions: 117mm (L), 33mm (R), and power supply: DC 5V via USB connector. The size of field of view is 33mm (sensor diagonal)/800(magnification)= 0.04125 mm. The focusing range is 4-1/2" (115mm) and the dimensions are 117mm (L) and 33mm (R). A desktop computer with i5 (3.40 GHz), 8 GB RAM, NVIDIA GeForce GTX 1060 6G GPU is used in running the code. The entire experimentation has been conducted on three different software systems.

1. Pluggable Digital Viewer: This tool is primarily used to gather data for the model by gathering images from the digital microscopy camera sensor.
2. Juypter Notebook: The preprocessing of data, creation of the WPCNet CNN model, training of the CNN model, and integration of the CNN model with the Cascade classifier have all been done on this Python framework.
3. Cascade Trainer GUI: This software mainly used for training the Cascade classifier with positive and negative images.

4. WEAR PARTICLE CLASSIFICATION

The process of wear particle classification can be divided into three stages. In the first stage the data pre-processing is carried out, in the second stage the process of defining and training the WPCNet CNN model is carried out and in the third stage the classification of wear particles using WPCNet is carried out. The complete process is shown in Figure 5.

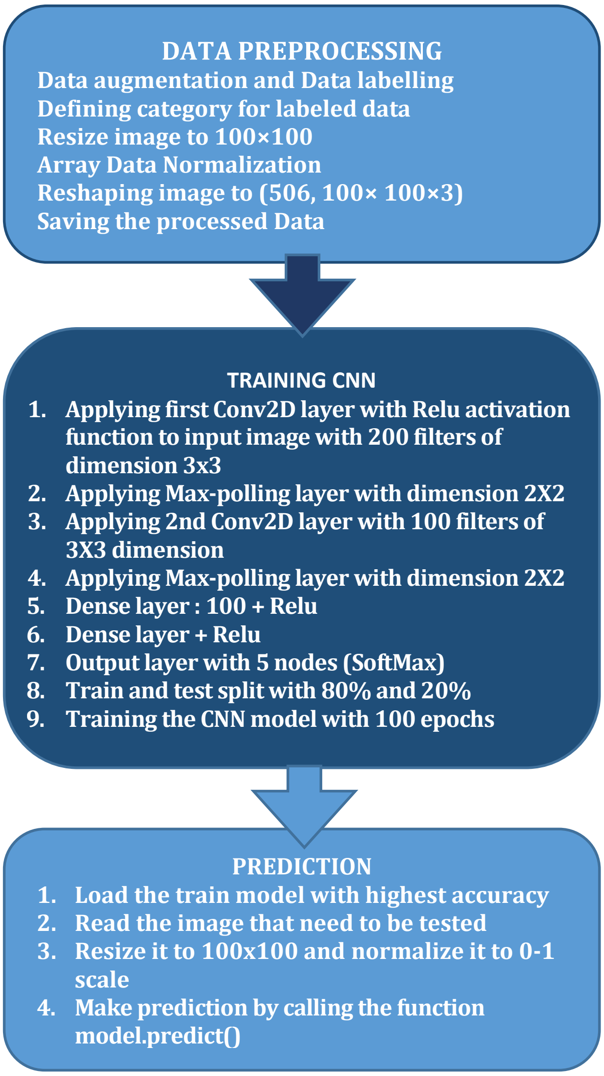
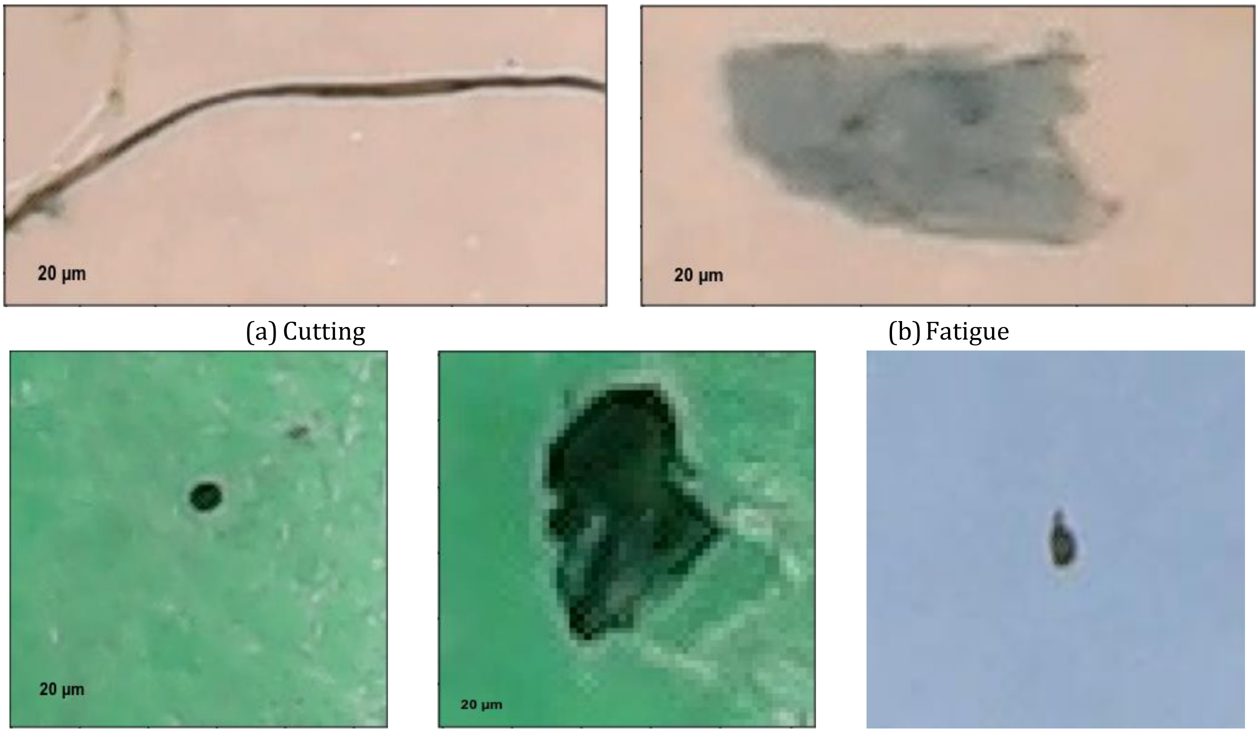


Fig. 5. Three stages of wear particle classification.

4.1 Data Pre-processing

To reduce the computation time and its complexity, the data needs to be pre-processed first, so that the data fits efficiently to the model for training purposes. In the experiment, five types of wear particles are collected from the lubricant of the gear box by using a 800x zoom digital microscope camera and categorized as cutting, spherical, fatigue, rubbing and severe sliding as shown in Figure 6.



(a) Cutting (b) Fatigue

(c) Spherical (d) Severe Sliding (e) Rubbing

Fig. 6. Typical wear debris types,

The parameters which are used for the pre-processing are Data augmentation, Resizing all data to a particular size, Array data normalization, Reshaping data to appropriate shape and finally shaving data to Data and Target variable. Data augmentation means increasing the size of collected data by changing the orientation and size of the actual image. Resizing all data to a particular size is necessary as collected data can be of different sizes which cannot be sent directly for the training purpose. Data normalization is required in bringing the value of input array from range 0-255 to range 0-1 to reduce the computation resource. Reshaping data to appropriate shape is necessary so that data can fit efficiently to the model during the training process.

4.2 Training CNN

Second stage consists of defining and training the CNN model. CNN can be defined as a multi-layer neural network where layers include input layer, convolutional layer, pooling layer, flatten layer, fully connected layer and output layer. The convolutional layer has special capability to extract multidimensional features from a given image by applying multiple filters on it which enables the use of CNN in the fields where manual extraction of multidimensional features is difficult which broadens the application area of CNN. Some of available network models are AlexNet, ResNet, GoogleNet, Cifar10 and VGG. As these network complexities are high and they are trained on large datasets, it requires lots of computation resources and training time. An improved light weight integrated CNN model is presented in this paper. Eight parameters: data argumentation, loss function as categorical_crossentropy, optimizer as Adam and 200 of size 3x3 convolution kernel are used to speed up the model and to increase the detection and classification accuracy. The WPCNet consists of five layers which includes two convolutional layers with Relu as activation function and three fully connected layers. The model was trained using a sample set of 36 people. These 36 wear particle images were collected, and through data augmentation, the number was raised to 506, with a division of 80% for training and 20% for testing.

4.3 Prediction

In the prediction stage, first the model is loaded with the highest accuracy to achieve the more accurate result in every test. The images need to be read in the python environment through a python package like OpenCV and then the images need to be resized to the same size of input image at the time of CNN training. The normalization is applied to the input image array to bring the array value in rage of 0 to 1 and then finally prediction can be made with respect to the input image by calling the function model.pridict(), this will result to the classification of input image in any one category out of five that is cutting, fatigue, sliding, rubbing and spherical. The wear particles were obtained from the experimental setup described in section 3.

5. RESULTS AND DISCUSSION

5.1 Data Augmentation

The Data Augmentation is a method of amplifying the dataset or to increase the numbers of data from its original size by changing its orientation and size. The different orientation parameters available in data augmentation are skew, rescaling, rotation, flipping, shearing etc. The different parameters settings used in this experiment are provided in Table 2.

Table 2. Parameters setting for data augmentation method.

Method	Settings
Rotation	Range - 40
Rescaling	0.2
Flipping	vertical
Flipping	horizontal
Shearing	Range- 0.2
Skew	Random with magnitude 0.8
Mode	Nearest

The data augmentation in this experiment enables the data set to increase from 36 to 506 and the different transformed image by data augmentation is shown in Figure 7.

The different training parameters in this experiment are activation function with conv layer: relu, dropout: 0.5, activation function for output layer: SoftMax, max epochs: 100, loss function: categorical_crossentropy, optimizer: Adam. The results are shown in Figure 8 and 9.

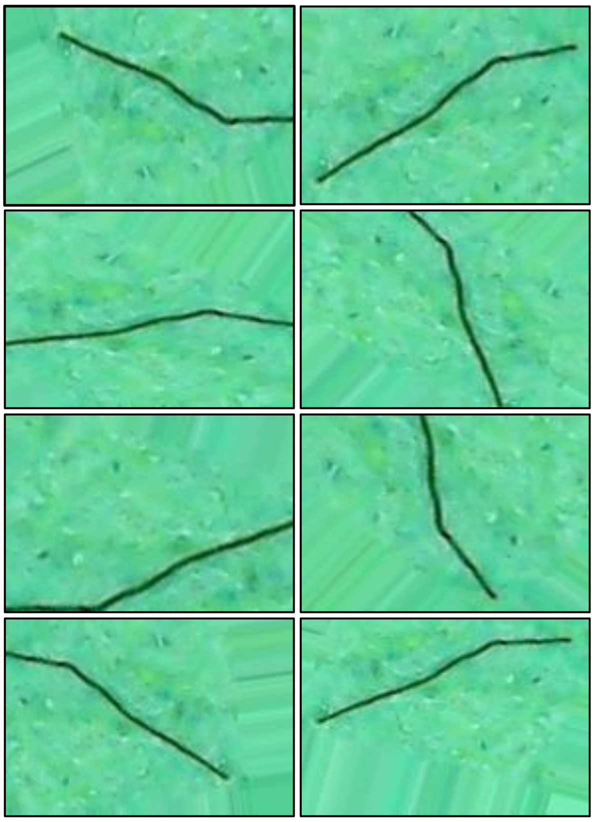


Fig. 7. Wear particle **v**iews of different types of transformation.

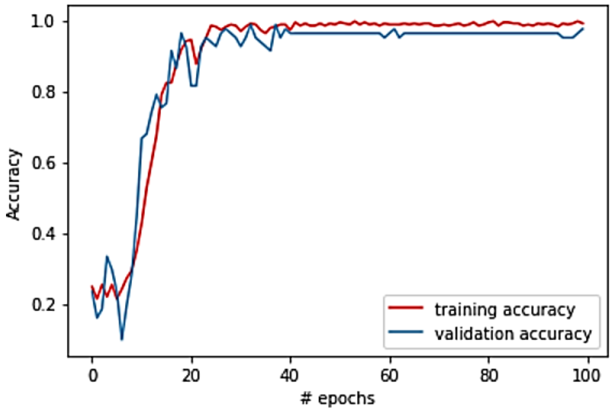


Fig. 8. The accuracy vs epochs curve.

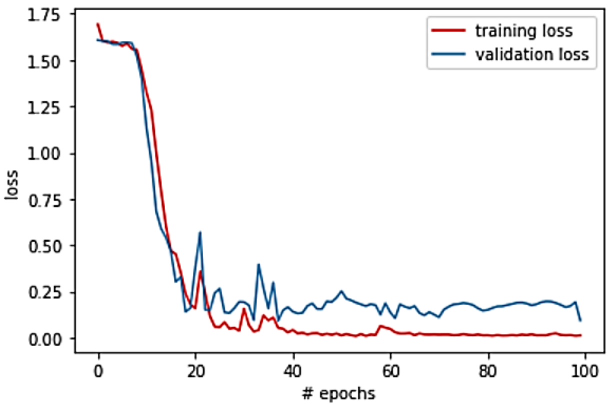


Fig. 9. The loss vs epochs curve.

It is observed that the training accuracy is in consonance with the validation accuracy. However, there is slightly increased validation loss as compared to the training loss.

5.2 Data Analysis

The basic WPCNet model consists of two convolutional layer and three fully connected layer. To investigate the performance of WPCNet in different scenarios different parameters are set with basic WPCNet and result is analysed at the end which indicates that it is achieving its highest accuracy with Adam as optimizer, loss function as categorical_crossentropy and SoftMax as output layer activation function.

Multiple trials are run with multiple epochs to prevent the contingency, as shown in Figure 10.

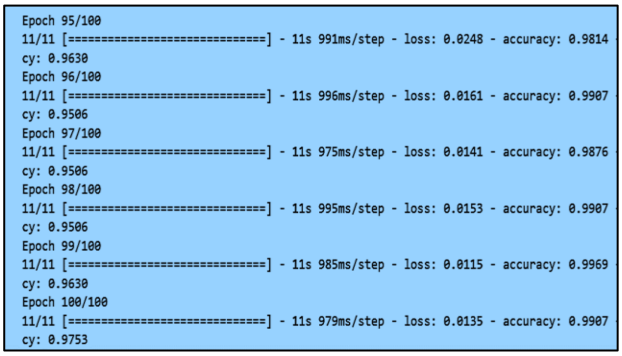


Fig. 10. Trial runs with multiple epochs.

With the same configuration as WBCNet, several experiments were conducted with some predefined models like AlexNet, GoogleNet & Ciphar10 and it is observed that WBCNet achieves the highest accuracy of 97.4% with less training time and less computation resources. The comparison result of different models with WPCNet is given in Table 3.

Table 3. Comparison of WPCNet with different models.

Model	Layers	Training time (min)	Validation accuracy (%)	Test accuracy (%)
GoogleNet	22	37	93.2	90
Cifar10	05	06	87.6	83
AlexNet	08	1477	91	89
WPCNet	05	20	97.4	97

The performance of WPCNet CNN model is evaluated by the help of the confusion matrix as shown in Figure 11.

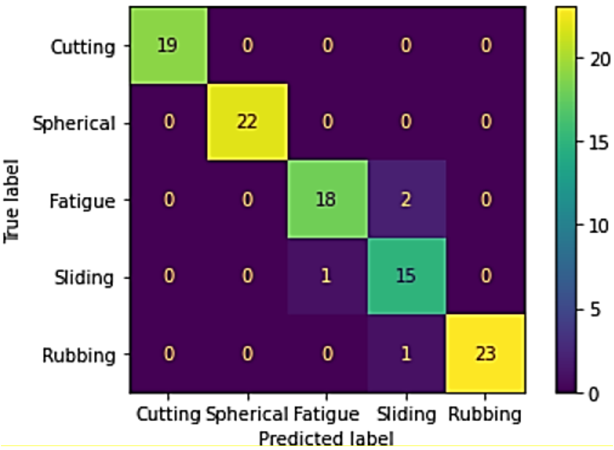


Fig. 11. The Confusion Matrix

It is observed that this model is highly efficient for classification as almost all classifications made by this model are correct except four incorrect classifications. In all, 19 cutting particles were classified as cutting, 22 were classified as spherical particle, out of 20 fatigue particle 18 are classified as fatigue, out of total 16 sliding particle 15 are classified as sliding and out of 24 rubbing particles, 23 are classified as rubbing particles.

5.3 Live Detection of Wear Debris

For the detection and successful classification, CNN model is integrated with cascade classifier so that once the wear debris is detected using trained cascade classifier it can use the WPCNet model to successfully classify it into different five categories. Cascade classifier is basically known for object detection purposes where lots of images of the object as positive image and image without object as negative image are provided to the cascade function for the training purpose. In this experiment, the Cascade-Trainer-GUI software is used to train the classifier where a total 506 particle images were provided as positive images with 100 percent of usages and 1000 images without particles as negative images to get better detection. The other different parameters used for training in Cascade-Trainer-GUI are shown below in Table 4.

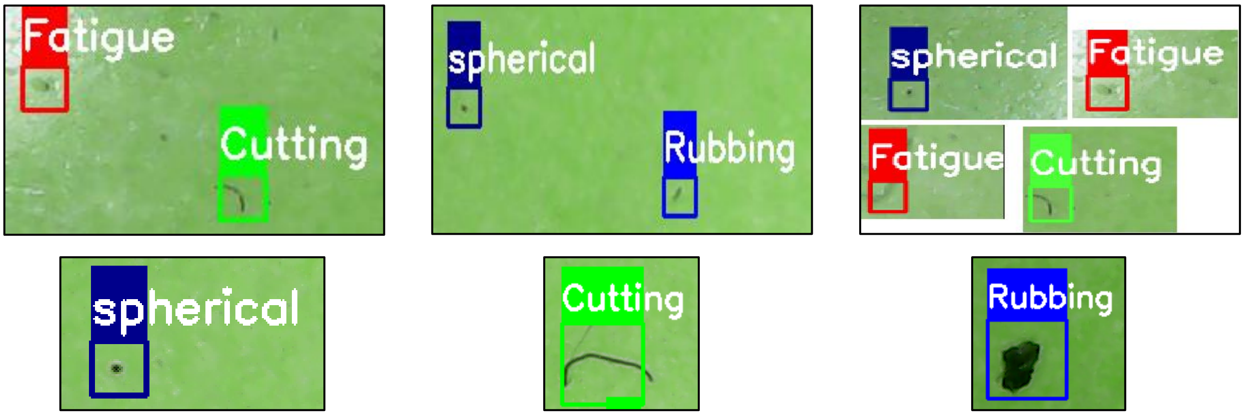


Fig. 12. Wear debris detection and classification.

Table 4. Parameters used for training in Cascade-Trainer-GUI.

Parameters	Value
Force positive sample count	1
Number of stages	20
Number of threads	5
Acceptance ratio break value	-1.0
Sample width	24
Sample height	24
Feature type	HAAR
HAAR Feature type	Basic
Boost Type	CAB
Minimal hit rate	0.9950000
Maximum False alarm rate	0.5000000
Weight Trim rate	0.9500000
Maximal depth weak tree	1,0000000
Maximal weak trees	100

Upon the successful training of the cascade classifier, the trained model with .xml extension is generated which is then later used to integrate with the CNN model WPCNet so that the classification of the detected particle can be done successfully. The result of detection and classification of different wear debris are shown in Figure 12.

The use of this model as an efficient method for continuous monitoring of gear wear particles in any industrial machinery is one potential practical implementation of the current research. All the problems encountered traditionally can be solved by the integrated technique of customized lightweight CNN model WPCNet with Cascade classifier.

6. CONCLUSIONS

In this research work, an integrated model of cascade classifier with light weight WPCNet CNN model is proposed to achieve the purpose of live detection and classification of wear particles with high accuracy. This model can be utilized to build a solution for continuous monitoring of gear wear particles in any industrial machinery. The integrated method of customized light weight CNN model WPCNet with Cascade classifier overcomes all the difficulties faced traditionally. It is observed that an accuracy of 97.4% is achieved by WPCnet model and this model is used to integrate with trained cascade classifier to detect and classify the wear debris particles accurately. The CNN model is more efficient than the traditional methods because it allows automation of the entire process by automatically extracting features from images by putting multiple filters on it. Conventional techniques require manual feature extraction, which makes the entire process laborious and inefficient. It is concluded on the basis of the results that WPCNet CNN integrated with cascade classifier is the most efficient classification model for the wear particle classification. This fulfils the aim of automating the complete process of detection and classification of wear particle in live scenario.

7. FUTURE SCOPE

The future objectives of the current work include the creation of a distinct cell with three to four cameras to take real time images of the of wear debris. These images would be processed to create a solid model of each particle which will then be combined to create a reconstructed worn-out gear pair model needed for the digital twin. Depending on the availability of sophisticated instrumentation and related software, the precise study course will be chosen.

REFERENCES

[1] Z. Peng, T.B. Kirk, *Wear particle classification in a fuzzy grey system*, Wear, vol. 225–229, pp. 1238–1247, 1999, doi: 10.1016/S0043-1648(98)00400-1

[2] S. Raadnui, *Wear particle analysis-utilization of quantitative computer image analysis: A review*, Tribology International, vol. 38, iss. 10, pp. 871–878, 2005, doi: 10.1016/j.triboint.2005.03.013

[3] J. Wang, X. Wang, *A wear particle identification method by combining principal component analysis and grey relational analysis*, Wear, vol. 304, iss. 1-2, 2013, doi: 10.1016/j.wear.2013.04.021

[4] W. Yuan, K.S. Chin, M. Hua, G. Dong, C. Wang, *Shape classification of wear particles by image boundary analysis using machine learning algorithms,* Mechanical Systems and Signal Processing, vol. 72-73, pp. 1–13, 2015, doi: 10.1016/j.ymssp.2015.10.013

[5] Y. Peng, J. Cai, T. Wu, G. Cao, N. Kwok, S. Zhou, Z, Peng, *A hybrid convolutional neural network for intelligent wear particle classification*, Tribology International, vol. 138, pp. 166–173, 2019, doi: 10.1016/j.triboint.2019.05.029

[6] P. Peng, J. Wang, *Wear particle classification considering particle overlapping*, Wear, vol. 422–423, 2018, pp. 119–127, 2019, doi: 10.1016/j.wear.2019.01.060

[7] X. Liu, L. Cheng, G. Chen, X. Wang, J. Wang, *Recognition of fatigue and severe sliding wear particles using a CNN model with multi-scale feature extractor*, Industrial Lubrication and Tribology, vol. 74, iss. 7, pp. 884–891, 2022, doi: 10.1108/ILT-03-2022-0088

[8] V. Reddy, C. Sanderson, B.C. Lovell, *Improved Foreground Detection via Block-Based Classifier Cascade With Probabilistic Decision Integration*, IEEE Transactions on Circuits and Systems for Video Technology, vol. 23, iss. 1, pp. 83–93, 2013, doi: 10.1109/TCSVT.2012.2203199

[9] S. Bej, R. Das, H. Hirani, S. Ghosh, P. Banerjee, *"Naked-eye" detection of CN– from aqueous phase and other extracellular matrices: an experimental and theoretical approach mimicking the logic gate concept*, New Journal of Chemistry, vol. 43, iss. 46, pp. 18098–18109, 2019, doi: 10.1039/C9NJ04528G

[10] M.S. Laghari, Q.A. Memon, G.A. Khuwaja, *Knowledge based wear particle analysis*, International Journal of Information Technology, vol. 1, iss. 3, pp. 91–95, 2007, doi: 10.5281/zenodo.1084732

[11] V.D. Gonçalves, L.F. De Almeida, M.H. Mathias, *Wear particle classifier system based on an artificial neural network*, Strojniški vestnik-Journal of Mechanical Engineering, vol. 56, iss. 4, pp. 277–281, 2010.

[12] R. Juránek, S. Machalík, P. Zemčík, *Analysis of Wear Debris Through Classification*, in 13th International Conference on Advanced Concepts for Intelligent Vision Systems, ACIVS 2011, 22-25 August, 2011, Ghent, Belgium, pp. 273-283, doi: 10.1007/978-3-642-23687-7

[13] H. Hirani, K. Athre, S. Biswas, *Comprehensive design methodology for an engine journal bearing*, Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology, vol. 214, iss. 4, pp. 401–412, 2000, doi: 10.1243/1350650001543287

[14] H. Liu, H. Wei, H. Xie, L. Wei, F. Li, *Unsupervised segmentation of wear particle's image using local texture feature,* Industrial Lubrication and Tribology, vol. 70, iss. 9, pp. 1601–1607, 2018, doi: 10.1108/ILT-09-2017-0275

[15] S. Sengupta, M. Murmu, S. Mandal, H. Hirani, P. Banerjee, *Competitive corrosion inhibition performance of alkyl/acyl substituted 2-(2-hydroxybenzylideneamino) phenol protecting mild steel used in adverse acidic medium: A dual approach analysis using FMOs/molecular dynamics simulation corroborated experimental findings*, Colloids and Surfaces A: Physicochemical and Engineering Aspects, vol. 617, 2021, doi: 10.1016/J.COLSURFA.2021.126314

[16] S.S. Goilkar, H. Hirani, *Parametric study on balance ratio of mechanical face seal in steam environment*, Tribology International, vol. 43, iss. 5–6, pp. 1180–1185, 2010, doi: 10.1016/j.triboint.2009.12.019

[17] H. Wang, F. Yuan, L. Gao, R. Huang, W. Wang, *Wear Debris Classification and Quantity and Size Calculation Using Convolutional Neural Network*, Communications in Computer and Information Science, vol. 1137, pp. 470–486, 2019, doi: 10.1007/978-981-15-1922-2_33

[18] E. Raschman, R. Záluský, D. Ďuračková, *New digital architecture of CNN for pattern recognition*, Journal of Electrical Engineering, vol. 61, no. 4, pp. 222–228, 2010, doi: 10.2478/v10187-010-0031-6

[19] C.R. Qi, H. Su, M. Niebner, A. Dai, M. Yan, L.J. Guibas, *Volumetric and multi-view CNNs for object classification on 3D data*, in IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 27-30 June, 2016, Las Vegas, NV, USA, pp. 5648–5656, doi: 10.1109/CVPR.2016.609

[20] M. Liang, X. Hu, *Recurrent convolutional neural network for object recognition*, in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 7-12 June, 2015, Boston MA, doi: 10.1109/CVPR.2015.7298958

[21] Q. Geng, Z. Zhou, X. Cao, *Survey of recent progress in semantic image segmentation with CNNs*, Science China Information Sciences, vol. 61, iss. 5, pp. 1–18, 2018, doi: 10.1007/s11432-017-9189-6

[22] F. Radenovic, G. Tolias, O. Chum, *Fine-Tuning CNN Image Retrieval with No Human Annotation*, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 41, iss. 7, pp. 1655–1668, 2019, doi: 10.1109/TPAMI.2018.2846566

[23] T. Takikawa, D. Acuna, V. Jampani, S. Fidler, *Gated-SCNN: Gated shape CNNs for semantic segmentation*, in IEEE International Conference on Computer Vision, 27 October -2 November, 2019, Seoul, Korea, pp. 5228–5237, 2019, doi: 10.1109/ICCV.2019.00533

[24] A. Khan, A. Sohail, U. Zahoora, A.S. Qureshi, *A survey of the recent architectures of deep convolutional neural networks*, Artificial Intelligence Review, vol. 53, iss. 8, pp. 5455-5516, 2020, doi: 10.1007/s10462-020-09825-6

[25] F. Sultana, A. Sufian, P. Dutta, *Evolution of Image Segmentation using Deep Convolutional Neural Network: A Survey*, Knowledge-Based Systems, vol. 201–202, 2020, doi: 10.1016/j.knosys.2020.106062

[26] W.S. Ahmed, A.A. Karim, *The Impact of Filter Size and Number of Filters on Classification Accuracy in CNN*, in International Conference on Computer Science and Software Engineering, 16-18 April 2020, University of Duhok, Duhok, Kurdistan Region, Iraq, pp. 88–93.: doi: 10.1109/ CSASE48920.2020.9142089

[27] R. Azad, A.R. Fayjie, C. Kauffmann, I.B. Ayed, M. Pedersoli, J. Dolz, *On the texture bias for few-shot CNN segmentation*, in IEEE Winter Conference on Applications of Computer Vision, WACV, 3-8 January, 2021, Waikoloa, HI, USA, pp. 2673–2682, doi: 10.1109/WACV48630.2021.00272

[28] H. Wang, H. Zuo, Z. Liu, D. Zhou, H. Yan, X. Zhao, M. Pecht, *Online monitoring of oil wear debris image based on CNN*, Mechanics and Industry, vol. 23, no. 9, pp. 1–15, 2022, doi: 10.1051/meca/2022006

[29] F. Jia, F. Yu, L. Song, S. Zhang, H. Sun, *Intelligent Classification of Wear Particles Based on Deep Convolutional Neural Network*, Journal of Physics: Conference Series, vol. 1519, no. 1, pp. 1-14, 2020, doi: 10.1088/1742-6596/1519/1/012012

[30] H. Wu, T. Wu, Y. Peng, *Watershed-Based Morphological Separation of Wear Debris Chains for On-Line Ferro-graph Analysis*, Tribology Letters, vol. 53, pp. 411–420, 2014, doi: 10.1007/s11249-013-0280-1

[31] S. Poddar, N. Tandon, *Classification and detection of cavitation, particle contamination and oil starvation in journal bearing through machine learning approach using acoustic emission signals*, Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology, vol. 235, iss. 10, pp. 2137–2143, 2021, doi: 10.1177/1350650121991316

[32] S. Mohanty, S. Hazra, S. Paul, *Intelligent prediction of engine failure through computational image analysis of wear particle*, Engineering Failure Analysis, vol. 116, 2020, doi: 10.1016/j.engfailanal.2020.104731

[33] S. Wang, T.H. Wu, T. Shao, Z.X. Peng, *Integrated model of BP neural network and CNN algorithm for automatic wear debris classification*, Wear, vol. 426–427, 2018, pp. 1761–1770, 2019, doi: 10.1016/j.wear.2018.12.087

[34] A.D.H. Thomas, T. Davies, A.R. Luxmoore, *Computer image analysis for identification of wear particles*, Wear, vol. 142, iss. 2, pp. 213–226, 1991, doi: 10.1016/0043-1648(91)90165-Q

[35] G.P. Stachowiak, G.W. Stachowiak, P. Podsiadlo, *Automated classification of wear particles based on their surface texture and shape features*, Tribology International, vol. 41, iss. 1, pp. 34–43, 2008, doi: 10.1016/j.triboint.2007.04.004

[36] Z. Peng, N.J. Kessissoglou, M. Cox, *A study of the effect of contaminant particles in lubricants using wear debris and vibration condition monitoring techniques*, Wear, vol. 258, iss. 11-12, pp. 1651–1662, 2005, doi: 10.1016/j.wear.2004.11.020

[37] C. Hu, W.A. Smith, R.B. Randall, Z. Peng, *Development of a gear vibration indicator and its application in gear wear monitoring*, Mechanical Systems and Signal Processing, vol. 76–77, pp. 319–336, 2016, doi: 10.1016/j.ymssp.2016.01.018

[38] L. Wang, Z. Zhang, *Automatic Detection of Wind Turbine Blade Surface Cracks Based on UAV-Taken Images*, IEEE Transactions on Industrial Electronics, vol. 64, iss. 9, pp. 7293–7303, 2017, https://doi: 10.1109/TIE.2017.2682037

[39] Y. Peng, J. Cai, T. Wu, G. Cao, N. Kwok, Z. Peng, *WP-DRnet: A novel wear particle detection and recognition network for automatic ferrograph image analysis*, Tribology International, vol. 151, 2020, doi: 10.1016/j.triboint.2020.106379

[40] X. Liu, J. Wang, K. Sun, L. Cheng, M. Wu, X. Wang, *Semantic segmentation of ferrography images for automatic wear particle analysis*, Engineering Failure Analysis, vol. 122, pp. 1–11, 2021. doi: 10.1016/j.engfailanal.2021.105268

[41] H. Hirani, K. Athre, S. Biswas, *Lubricant shear thinning analysis of engine journal bearings*, Tribology Transactions, vol. 44, iss. 1, pp. 125–131, 2001, doi: 10.1080/10402000108982435

[42] P. Kumar, H. Hirani, A. Kumar Agrawal, *Effect of gear misalignment on contact area: Theoretical and experimental studies*, Measurement, vol. 132, pp. 359–368, 2019, doi: 10.1016/J.MEASUREMENT.2018.09.070

[43] P. Kumar, H. Hirani, A.K. Agrawal, *Online condition monitoring of misaligned meshing gears using wear debris and oil quality sensors*, Industrial Lubrication and Tribology, vol. 70, iss. 4, pp. 645–655, 2018, doi: 10.1108/ILT-05-2016-0106

[44] G. Ciaburro, S. Padmanabhan, Y. Maleh, V. Puyana-Romero, *Fan Fault Diagnosis Using Acoustic Emission and Deep Learning Methods*, Informatics, vol. 10, iss. 1, pp. 183–204, 2023, doi: 10.3390/informatics10010024

[45] H. Hirani, *Multi-objective optimization of journal bearing using mass conserving and genetic algorithms*, Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology, vol. 219, iss. 3, pp. 235–248, Mar. 2005, doi: 10.1243/135065005X9844