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Article

An Intelligent Fault Diagnosis for Machine Maintenance using Weighted Soft-Voting Rule based Multi-Attention Module with Multi-Scale Information Fusion

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Abstract:

The ability of engineering systems to process multi-scale information is a crucial requirement in the development of an intelligent fault diagnosis model. This study develops a hybrid multi-scale convolutional neural network model coupled with multi-attention capability (HMS-MACNN) to solve both the inefficient and insufficient extrapolation problems of multi-scale models in fault diagnosis of a system operating in complex environments. The model's capabilities are demonstrated by its ability to capture the rich multi-scale characteristics of a gearbox including time and frequency multi-scale

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18   information. The capabilities of the Multi-Attention Module, which consists of an adaptive weighted

19   rule and a novel weighted soft-voting rule, are respectively integrated to efficiently consider the

20   contribution of each characteristic with different scales-to-faults at both feature- and decision-levels.

21   The model is validated against experimental gearbox fault results and offers robustness and

22   generalization capability with F1 value that is 27% higher than other existing multi-scale CNN-based

23   models operating in a similar environment. Furthermore, the proposed model offers higher accuracy

24   than other generic models and can accurately assign attention to features with different scales. This

25   offers an excellent generalization performance due to its superior capability in capturing multi-scale

26   information and in fusing advanced features following different fusion strategies by using Multi-

27   Attention Module and the hybrid MS block compared to conventional CNN-based models.

28   **Keyword:** Intelligent diagnosis; Prognosis and health management; Convolutional Neural Network;

29   Gearbox maintenance; Multi-scale information fusion; Fault diagnosis

30   I. INTRODUCTION

31   Future engineering systems need to be equipped with intelligent capabilities in order to improve

32   their efficiency and reduce operational costs through predictive maintenance. Selection of maintenance

33   methods for an equipment is an important consideration in its design life due to its consequence on

34   reduction of economic loss and safe utilization [1]. Available literatures suggest that the development

35   of an effective intelligent maintenance approach is receiving significant attention because of rapid

36   advancements in information technology (data analytics and internet of things) and its application to

37   maintenance industries [2].

38   Implementation of Prognosis and Health Management (PHM) capabilities in equipment and

39 machines based on information science is a vital part of the intelligent maintenance approach in the

40 information era. Fault diagnosis is a complimentary part of the PHM, whose task is to identify the

41 different failure modes of the equipment or machines [3]. In the structural health monitoring of a whole

42 machine, it is necessary to obtain information through multiple sensors in order to corroborate fault

43 diagnosis methods, such as in the monitoring of wind turbine operations. Most of the available studies

44 on corroborated fault diagnosis methods focus on the fusion of decision-making with multisensory

45 technologies [4], [5], [6], [7]. However, when monitoring the structural conditions of fine machine

46 components, the space requirement for installation of multi-sensors not only reduces equipment space

47 but also obscures the fault information measurement from both highly sensitive and insensitive sensors.

48 For instance, the bearing vibration of a wind turbine gearbox has sufficient fault information in its

49 main vibration direction [8], but the fault information included in other degrees of freedom (DOFs) is

50 insensitive to the fault patterns. Therefore, this needs fusion of extra decision methods to cover its

51 shortage to conduct effective fault diagnosis [9]. For the intelligent maintenance model to be capable

52 of improving the performance of the fault diagnosis of a system when using a single sensor, it will not

53 only have to solve the local faults on fine components during its condition monitoring but must also

54 lay the foundation for multi-sensor corroborative diagnosis of faults in large and fine components.

55 Therefore, this study focuses on how to achieve an efficient PHM for local mechanical system.

56   Recent development in methodologies for PHM are largely based on data-driven approaches,

57 which typically consist of feature extraction and pattern recognition. These approaches mostly rely on

58 accurate extraction of fault features from either time-domain or frequency-domain responses of raw

59 vibration data using signal processing algorithms, like the Empirical Mode Decomposition (EMD),

60   Local Mean Decomposition (LMD) or Variational Mode Decomposition (VMD) [10]. For example, a

61   gearbox's (taken as a partial component in a machine) main function is the sustenance or transmission

62   of dynamic loads on rotating engineering systems. Gearbox typically comprises of gears and bearings

63   and its operating nature makes it susceptible to failure due to defects or faults throughout its design

64   life. These faults and defects can undermine the operational viability of the entire mechanical system

65   or plant, underscoring the need for an intelligent diagnosis method for early detection of any likelihood

66   of fault or failure. The potentials for deformations in the gear and bearing will result in severe safety

67   issues and financial loss to the operators of the actual engineering systems [11].

68   In the pattern recognition phase, the features extracted from the signal of a faulty system are

69   processed using a machine learning models, such as the Logistic Regression model, Random Forest

70   (regression trees) or Support Vector Machine (SVM) to diagnose fault on gearbox. However, these

71   methods, especially those based on the two phases, have some fatal disadvantages. First, the extracted

72   features that are fed into the machine learning classifiers heavily rely on the knowledge and experience

73   of the users. The upper boundary of the fault diagnosis accuracy is limited by the effectiveness of the

74   extracted features in the data-driven method. Secondly, the generalization ability of a shallow network-

75   based diagnosis model is relatively poor, resulting in a significant difficulty for time-variant working

76   conditions with strong noise interference. Therefore, an alternative solution is urgently needed to

77   efficiently diagnose faults in an engineering system like the gearbox using the measured gearbox

78   signals.

79   Deep learning, based on a fusion of feature extraction and classification method, can deal with

80   the identified weaknesses in the traditional intelligent fault diagnosis methods by building a model

81 with high level of advanced features based on deep networks. A majority of generic deep learning

82 algorithms that are currently being widely used, like the Convolutional Neural Network (CNN) model

83 and Deep Belief Network (DBN) model [12], have been examined successfully in the fault diagnosis

84 of systems [13],[14],[15]. However, it is found that the end-to-end CNN-based model, which uses

85 unfiltered vibration responses, can be more effective than the generic fault identification methods

86 based on vibration images [16],[17]. In addition, most studies associated with the CNN-based fault

87 diagnosis method using unfiltered vibration response as input reveal that the fixed scale CNN-based

88 models for diagnosis did not perform well when they are applied to actual working conditions. This is

89 because the characteristics contained in raw vibration signals cannot be sustained on a certain inherent

90 scale where changes in the environments, sampling frequencies or systems exist. The main factors

91 affecting the performance of a multi-scale deep learning method's application in fault diagnosis

92 method are: 1. Extraction and obtaining sufficient information for fault identification; 2. Availability

93 of reasonable strategies for information fusion.

94 Consequently, Huang *et al.* developed a model called "multi-scale cascade convolutional neural

95 network", whose key idea was to use filters with different scales to provide more useful information

96 [18]. Their results show that considering multi-scale information is effective in improving the accuracy

97 of diagnosis and distinguishing the types of bearing faults. Furthermore, Liu *et al*. [19] added a residual

98 network module into the multi-scale neural network algorithm in order to improve its performance.

99 Their algorithm was designed by incorporating a multi-scale residual neural network, which improves

100 the model's good performance for motor fault diagnosis. In the above studies, although the locations

101 of the feature fusion are different, the processes of the multi-scale feature extraction are both realized

102 by changing the different receptive fields by the size of convolution kernels. In order to ensure that a

103 CNN-based model can capture multi-scale information in the widest possible receptive field, Zhao *et*

104 *al*. [20] used the dilated convolution operation to build a multi-scale CNN. The multi-scale factor acts

105 as the dilation factor of convolution kernel. The results show that the dilated multi-scale convolution

106 neural network has a good generalization in bearing fault diagnosis tasks. However, computational

107 complexity is increased when convolution kernels are applied directly to extract multi-scale

108 information from a raw signal. To solve this problem, Jiang *et al*. [21], used a 1-D vibration response

109 signals as the input data and further designed a diagnosis model using the multi-scale CNN (MS-CNN)

110 to diagnose gearbox faults of a wind turbine. Their multi-scale feature extraction was established by

111 the procedure of multi-scale coarse-grained rather than convolution kernels. The results indicated that

112 the time scale of the MS-CNN model offers a considerable influence on the effect of faults diagnosis

113 of the wind turbine gearbox model. Qiao *et al.* [22] designed an adaptive weighted multi-scale with

114 convolutional neural network model in order to conduct an end-to-end diagnosis for an end-to-end

115 bearing model. Their study show that the model offers a strong ability to distinguish faults and with an

116 adaptive ability for the domain against variable operating conditions. Qiao's model considers the

117 differences in contribution between features. Thus, they adaptively weighed the features of different

118 channels and then fused them together. This essentially introduces self-attention into the channels.

119 However, in the above-mentioned multi-scale studies for diagnosis, although multi-scale features are

120 directly fused together at feature-level, the differences in the contribution of advanced features in

121 probability calculation were not considered. Although Xu *et al*. [23] considered these differences in

122 their contribution to advanced feature extractions in probability calculation, they fused the advanced

123 features on the feature-level that would probably make the useful information meaningless when fusing

124 these advanced features with different scale levels. On the other hand, using non-continuous windows

125 to sample the multi-scale information causes an exponential decrease of the sub-signal's length,

126 leading to hard maintenance of the model and the loss of some important information. Bo *et al.* [24]

127 used separate convolution with depth attention and point attention to establish the multi-scale model

128 but also ignored the differences in the performance generated by the fusion-level in a model. Bias

129 prediction may occur because only a fully connected layer is used to calculate the patterns'

130 probabilities. Zhang *et al*. [25] consider the multiple patterns fused in feature-level may lack of

131 physical meanings. The authors developed a Particle Swarm Optimization (PSO) based weighted

132 majority voting rule to fuse the diagnosed labels in decision-level. However, the PSO-based algorithm

133 is liable to being interwoven and interrupted by other algorithms.

134   To address the above-mentioned problems, an intelligent diagnosis model based on a novel

135 weighted soft-voting rule-based Multi-Attention with Hybrid Multi-Scale Convolutional Neural

136 Network architecture (HMS-MACNN) is developed in this study. This new model is aimed at solving

137 fault diagnosis problems as demonstrated by its successful application in diagnosing gearbox faults.

138 This paper offers the following specific contributions:

139   1) An integrated multi-scale block, named Hybrid Multi-Scale (HMS) block, combined the

140 capabilities of multi-scale coarse-grained procedure and different convolutions to simultaneously

141 capture both time multi-scale and frequency multi-scale information of raw vibration signals.

142   2) An innovative multi-scale CNN-based network (HMS-MACNN) has been proposed to solve

143 the inherent limitations of current methods used in the diagnosis of faults in complex engineering

144 system like a gearbox. HMS-MACNN is integrated with multi-scale coarse-grained procedures and

145 dilated convolutions to collectively obtain features from raw vibration signals from a system (gearbox)

146 using multiple scales.

147   3) The proposed multi-Attention block is applied to evaluate the contributions of the hybrid multi-

148 scale features that follows the multi-scale rank in the HMS block, except for channel attention. Multi-

149 Attention block built with two parts including frequency weighted and fused in feature-level and time

150 multi-scale with advanced features weighted and fused in decision-level. This enhances the algorithm'

151 capabilities in the avoidance of undifferentiated and blind features fusion in existing models in

152 accordance with fusion strategies. The decision process in the multi-Attention block consists of a

153 proposed weighted soft-voting rule and an adaptive weighted rule, in which the weighted scores

154 calculated by the weighted soft-voting rule are optimized by a gradient descent without the intervention

155 of other algorithms.

156   4) As an end-to-end model, the HMS-MACNN is designed by adopting the advantages offered

157 by the 1-D CNN-based model and then extending such benefits to include ability to obtain damage

158 features and diagnose faults from raw vibration signals without applying any manual modifications.

159   5) This newly developed method improves efficiency and reliability of fault diagnosis tools by

160 returning no false positive results. The method is validated through experimental simulations of

161 gearbox with faults to examine the performance of the newly developed method. The superiority of

162 the HMS-MACNN is further demonstrated through comparison with results from published studies on

163 multi-scale diagnosis models.

164   Following the introduction, subsequent sections of the paper are structured as follows.

165 Development of the HMS-MACNN framework is presented in Section 2, while Experimental data and

166 evaluation index are presented in Section 3. Validation, presentation of results and discussion on the

167 HMS-MACNN model under different working conditions are presented in Section 4. Conclusions are

168 presented in Section 5.

II. PROPOSED METHOD

170   The main constituents of the newly developed intelligent fault diagnosis method are Hybrid

171 Multi-Scale function; a CNN based model, a Multi-Attention Module which consists of an adaptive

172 weighted rule and the proposed weighted soft-voting rule. These components are integrated together

173 to develop the hybrid Multi-Scale CNN with Multi-Attention Architecture. Details of the mathematical

174 formulation, stand-alone performance and capability and the procedure for integrating them in the

175 novel architecture are presented in the following sections.

A. HYBRID MULTI-SCALE

177   The current methods used for deep learning model-based studies of fault diagnosis of engineering

178 systems use raw vibration signals as the inputs. The reliance of this approach on the raw signal as the

179 main input of the networks essentially constitute a classification or regression problem rather than a

180 diagnosis. However, these models always perform poorly under complex environments such as those

181 with variable loads and strong noises. This is because the CNN-based models have a fixed sampling

182 scale, which can only capture information from a single scale. Therefore, the effective information for

183 fault diagnosis will not remain in an inherent scale when the operating environment changes [26].

184 Learning the characteristics of a single scale will lead to poor generalization of a model.

185   The key to overcoming this shortcoming and improving the generalization capability of a CNN-

186   based model is to enhance the model's capability in capturing multi-scale characteristics. Some studies

187   have proposed multi-scale based models, such as MSCNN and MCCNN, which both of them only

188   consider multi-scale characteristics in time and frequency domains independently [15],[18],[21].

189   However, both time- and frequency-domains multi-scale characteristics are important for fault

190   detection.

191   Therefore, this study proposed a hybrid multi-scale block (HMS) to be coupled with a CNN model

192   in order to address the fault diagnosis generalization problem. In addition, this method will improve

193   accuracy, efficiency and reliability of fault diagnosis in noisy environments and for systems under

194   complex health and operating environments. A diagram of the hybrid multi-scale block, which consists

195   of the multi-scale coarse-grained procedures [27] and dilated convolutions [28], is illustrated in Figure

196   1.
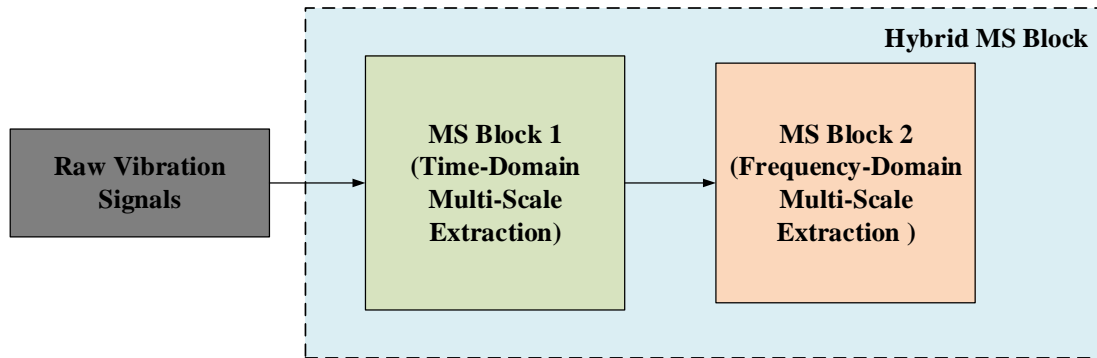
Figure:1 An illustration of Hybrid MS Block

197   As shown in Figure 1, two multi-scale (MS) blocks are connected in series to form a hybrid MS

198   block. In the hybrid MS block, the MS block1 is used to capture multi-scale features in time domain

199   by using a novel multi-scale coarse-grained procedure. The designed MS block2 is used to extract

200   more useful information in the multi-scale time-frequency domain from the sub-signals that are

201 obtained by the MS block1. It should be noted that the convolution kernel in MS block2 is of fixed

202 size and the dilated parameters are changed, causing it to have a larger receptive field in a limited

203 amount of data.

204   Jiang *et al.* [21] used the MS coarse-grained procedure to extract time-domain multi-scale

205 characteristics, but they used the non-continuous window to sample the features, which significantly

206 drops the length of sub-signals and probably misses key information. Thus, MS block1 is designed

207 based on the MS coarse-grained procedure for multi-scale time feature extraction based on improved

208 principles of multi-scale coarse-grained procedure. In addition to being motivated by Zhang *et al.*'s

209 research [29], this study uses a training inference approach in order to improve the MS block1's

210 capability and the model's robustness by using random data point removal technique to augment multi-

211 scale coarse-grained procedure.

212   The MS block 1 works using a vibration signal in which the response is averaged through a

213 continuous sliding window. In an attempt to improve the designed model's noise resistance, some data

214 points are discarded based on the dropout technique coupled with the procedure of coarse-grained in

215 the training model design phase. The dropout rate p is a selected value set at 0.5.

216   For each raw vibration signal $x_i : 1 \le i \le n$, the sub-signal. y_j. is obtained by MS block1 at any

217 scale *s* and is calculated by Eq (1).

$$
\begin{aligned}
& r_i^1 \sim Bernoulli(p) \\
& \tilde{x}^l = r_i^1 \cdot x^l \\
& y_j = \begin{cases} \dfrac{1}{\tau} \sum\limits_{i=(j-1)+1}^{(j-1)+1+\tau} \tilde{x}(i), j \in [1, n\text{-}\tau] \\ y_j = \dfrac{1}{\tau} \tilde{x}(i)\, j \in [n\text{-}\tau, n] \end{cases}, \tau \ge 2
\end{aligned}
\tag{1}
$$

218 where $\tau = 2, 3, \ldots, s$ is the factor of scale in MS block1. "$\cdot$" is the element product, r_i^1 follows

219 Bernoulli distribution, which decides whether the data points x^l in the multi-scale coarse-grained

220 procedures $\tilde{x}^l$ has dropped out or not. The length of the sub-signal y_j is n.

221   In the MS block 2, dilated convolutions with different dilated factors υ are used to extract

222 frequency-domain's multi-scale information. The receptive field calculation of the dilated convolution

223 layer is shown in Eq (2).

$$R = K + (K - 1) \cdot (\upsilon - 1) \ , \ \upsilon \in 1, 2, \ldots, v \tag{2}$$

224 Where R is the receptive field of a convolution; K is the kernel size; υ is the dilated factor, which

225 controls the capability of the extraction of frequency-domain multi-scale characteristics.

226   The hybrid MS block initially obtains s time-domain multi-scale signals using MS Block1. The

227 frequency-domain multi-scale information is extracted by MS Block2 from each multi-scale sub-signal

228 in time domain. Total $s \cdot v$ sub-signals with multi-scale in both time and frequency domains will be

229 obtained by the proposed HMS block.

230 ## B. CONVOLUTIONAL NEURAL NETWORK

231   The feature learning layer consists of parallels of 1D CNNs that extracts representative features

232 from the sub-signals. Generally, the structure of a typical CNN structure comprises of various pairs of

233 convolutional layers, pooling layers, Batch Normalization ((BN)) block and action function. The

234 mathematical process of designing the CNN is given as follows:

$$y^{l(i,j)} = \mathbf{K}_i^l \cdot \mathbf{X}^{l(\mathrm{R}^j)} = \sum_{j'=0}^{W} \mathbf{K}_i^l(j')\mathbf{X}^{l(j+j')} \tag{3}$$

235 where $\mathbf{K}_i^l$ is the ith filter in the layer l, and $\mathbf{X}^{l(\mathrm{R}^j)}$ is the jth local area of the CNN's layer l;

236    $y^{l(i,j)}$ denotes the dot product of the filter and the Kernel's local area, while W represents the

237   kernel's width. $\mathbf{K}_i^l(j')$ is the jth weight of kernel l.

238   ReLU activation function is added to the convolutional layer. The formula for calculating the

239   ReLU function is given in Eq. (4):

$$a^{l(i,j)} = f(z^{l(i,j)}) = \max\{0, z^{l(i,j)}\} \tag{4}$$

240   Where $z^{l(i,j)}$ is the calculated output array of the BN and $a^{l(i,j)}$ is the activation of $z^{l(i,j)}$.

241   In order to efficiently facilitate the neural network training and to overcome gradient

242   disappearance problems caused by activation function, the BN technique is introduced before the

243   pooling operation. The n-dimensional array $\mathbf{y}^l = (y^{l(1)}, y^{l(2)}, \ldots, y^{l(n)})$ to the lth BN layer is represented

244   as $\mathbf{y}^{l(i)} = (y^{l(i,1)}, y^{l(i,2)}, \ldots, y^{l(i,n)})$ and $\mathbf{y}^{l(i)} = y^{l(i)} = y^{l(i,1)}$ when the BN layer is positioned

245   immediately after the convolutional layer in the model and followed by the fully connected layer. The

246   BN operation is mathematically represented by the following equations:

$$\hat{y}^{l(i,j)} = \frac{y^{l(i,j)} - \mu}{\sqrt{\sigma^2 + \varepsilon}}, z^{l(i,j)} = \gamma^{l(i)} \hat{y}^{l(i,j)} + \beta^{l(i)} \tag{5}$$

$$\mu = \frac{1}{n} \sum_{i=1}^{n} y^{l(i,j)} \tag{6}$$

$$\sigma^2 = \frac{1}{n} \sum_{i=1}^{n} (y^{l(i,j)} - \mu)^2 \tag{7}$$

247   where $z^{l(i,j)}$ represents the output of a single neuron, while μ and σ^2 are the respective mean and

248   variance of $y^{l(i,j)}$. ε is a negligible normalization quantity (constant) added to sustain the simulation

249   and stops any unexpected termination when the variance is 0. The scale factor and shift parameters to

250   be learned from the features are respectively represented by $\gamma^{l(i)}$ and $\beta^{l(i)}$.

251   A pooling layer, also called the down-sampling layer, is added to HMS-MACNN. This is based

252　on the most common pooling techniques that includes both average and maximum pooling. However,

253　this research chooses the maximum pooling, and it is presented in Eq (8).

$$p^{l(i,j)} = \max_{(j-1)W+1 \le t \le jW} \{a^{l(i,t)}\} \tag{8}$$

254　where $a^{l(i,t)}$ represents the value of the tth neuron in the ith framework of the sampling layer l;

255　The corresponding value of the neuron in layer l of the pooling is represented as $p^{l(i,j)}$, and

256　$t \in [(j-1)W+1, jW]$.

257　　　The probability distribution of the representative features extracted by CNN are fused and driven

258　into the connected classification layer. Each output is mapped into a probability by a softmax function

259　φ, which is define by:

$$\varphi(u_c) = e^{u_c} \Big/ \sum_{c=1}^{T} e^{u_c}, c = 1, 2, \ldots, T \tag{9}$$

260　where $\varphi(u_c)$ is a T-dimensional probability vector and denotes the probability distribution under T

261　kinds of test scenarios, u_c is the output from the CNNs.

262　## C. MULTI-ATTENTION MODULE FOR HYBRID MULTI-SCALE

263　　　The multi-scale features have different degrees of sensitivities to failure of gears and bearings

264　when operating in complex environments. However, the existing multi-scale fault diagnosis model

265　indiscriminately integrates the features, which are detrimental to the performance of the models.

266　Although there have been some reported studies on using adaptive weights to evaluate the

267　contributions of features, they essentially used channel attention to evaluate features without

268　considering the differences from contribution of multi-scale characteristics [30],[31].

269　　　An adaptive weighted rule, named Attention1 in Multi-Attention Module, is introduced as part of

270　the integration of the hybrid multi-scale with CNN to adaptively score and rank learned features at the

271 full scales. The implementation of the multi-attention also means that it can assign weights to extracted

272 features learned [32]. Consequently, MS blocks are designed to provide the basis for leaning from the

273 extracted features. The proposed Hybrid MS block consists of two multi-scale blocks. Thus, the

274 features learned by CNNs, which are extracted by MS block1 and MS block2, are weighted through

275 the attention mechanism in turns.

276   The features $\mathbf{O}_{S \cdot D} : O_1, \ldots, O_i, \ldots, O_{S \cdot D}$ learned from a segment of the raw signals are extracted by

277 HMS Block. A function $G(\cdot)$ has been added to them to obtain features $\mathbf{H}_{S \cdot D} : H_1, \ldots, H_i, \ldots, H_{S \cdot D}$.

$$H_{S \cdot D} = G(O_{S \cdot D}) = \sum_{i=1}^{M} O_{S \cdot D}(i) \tag{9}$$

278 where $O_{S \cdot D}$ is the ith output feature O_i, and M is obtained using convolution kernels' number obtained

279 from the preceding convolution operation.

280   An attention module's weights of extracted features on frequency-domain scale

281 $\alpha_{s \cdot 1}, \ldots, \alpha_{s \cdot d}, \ldots, \alpha_{s \cdot D}$ are obtained by using a fully connected layer coupled with a Softmax function

282 and they are calculated using Eq. (10).

283

$$\begin{cases} \alpha_{s \cdot d} = \text{Softmax}(\varphi_{s \cdot d}) = e^{\varphi s \cdot d} \Big/ \sum_{d=1}^{D} e^{\varphi s \cdot d} \\ \sum_{d=1}^{D} \alpha_{s \cdot d} = 1 \end{cases} \tag{10}$$

284 where $\varphi_{s \cdot d}$ is the fully connected layer's output. The weight of an extracted feature of each scale

285 $\alpha_{s \cdot d}$ is calculated using the Softmax function and they are mapped on a probability Space (0, 1),

286 adding to its intelligent capabilities.

287   The fusion of extracted features Z of MS block2 relating to α_k and O_k is calculated by Eq.

15

288 (11).

$$\mathbf{Z}_s = \sum_{d=1}^{D} \alpha_{s \cdot d} O_{s \cdot d}, s = 1, 2, \ldots, S \qquad (11)$$

289 Where, $\mathbf{Z}_s$ is the weighted features, which is fused by the frequency-domain multi-scale

290 characteristics.

291   The hybrid multi-scale block is used in the algorithm for the extraction of multi-scale features

292 based on time and frequency in turns. The multi-attention module is used to evaluate the contributions

293 of each advanced features of different scales for fault diagnosis. Different information fusion strategies

294 are used to fuse the time advanced features and frequency features. Thus, a novel weighted soft voting

295 method is proposed to fuse the advanced features at decision level. The weights of soft voting

296 procedure are updated by gradient descent with the network parameters updating.

297 *D. WEIGHTED SOFT-VOTING METHOD FOR ATTENTION ON DECISION-LEVEL*

298   The advanced features, with time a multi-scale fused at feature-level, will typically lack any

299 physical meaning. Thus, the proposed weighted soft-voting rule, named Attention2 in the Multi-

300 Attention Module, fuses the diagnosed results of the time multi-scale advanced features in decision-

301 making level.

302   The probability, $\mathbf{p} = p_1, \ldots, p_2, \ldots, p_s$ is calculated using a fully connected layer and normalized

303 by softmax function corresponding to features $\mathbf{Z}_s$. The final weighted probabilities are calculated by

304 Eq. (12)

$$\mathbf{p}_{weighted} = \mathbf{\alpha} \cdot \mathbf{p} = \sum_{s=1}^{S} \alpha_s^c \cdot p_s \bigg/ \sum_{s=1}^{S} \alpha_s^c \qquad (12)$$

16

305 Where $\mathbf{p}_{weighted}$ is the weighted probabilities for fault recognition; $\boldsymbol{\alpha}$ is the weight matrix for soft

306 voting fusion, which is solved by Gradient descent optimization; α_s^c is a weight vector with dimension

307 *c*, and *c* is the total categories.

308 The loss function of the HMS-MACNN model is a cross entropy between the output probability

309 distributions and predicted categories. The model uses $\mathbf{p}_{weighted}(x)$ as the predicted distribution

310 calculated by weighted soft-voting; $\mathbf{p}(x)$ is the predicted probability distribution that is fused directly,

311 and $\mathbf{q}(x)$ denotes the target probability distribution. The loss between $\mathbf{p}_{weighted}(x)$ and $\mathbf{q}(x)$ is

312 given by Eq. (13), while the loss between $\mathbf{p}(x)$ and $\mathbf{q}(x)$ is given by Eq. (14). Considering the loss

313 between $\mathbf{p}_{weighted}(x)$ and $\mathbf{p}(x)$, the loss function for solving parameters in weighted soft-voting rule

314 is given by Eq. (15)

315 The loss used to solve the parameters in the weighted soft-voting rule consists of

$$loss_w = -\sum_x p_{weighted}(x) \cdot \log q(x) \tag{13}$$

$$loss = -\sum_x p(x) \cdot \log q(x) \tag{14}$$

$$loss_{weighted} = -\sum_x p_{weighted}(x) \cdot \log q(x) - \sum_x p(x) \cdot \log q(x) + \sum_x p_{weighted}(x) \cdot \log p(x) \tag{15}$$

316 An illustration of how gradient descent is used to solve weights $\boldsymbol{\alpha}$ in the proposed weighted soft-

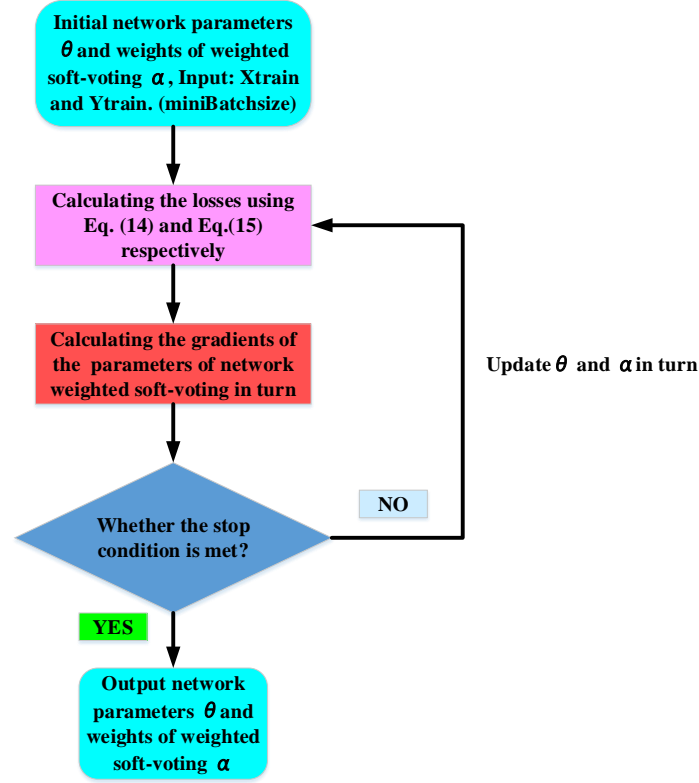317 voting method is shown in Figure 2.

Figure 2: Procedure for solving weights in the weighted soft-voting rule module

318   As shown in Figure 2, θ is the network's parameter, which is also a parameter in the HMS-

319   MACNN network in addition to parameter α in the weighted soft-voting rule. Two parts of the loss

320   are respectively calculated: a loss not contributing to the weighted soft-voting module; and the other

321   contributing to the weighted soft-voting. Equally, two gradients are calculated separately for each of

322   the losses. Before the iteration stops, the algorithm updates the parameters θ and α based on the

323   two gradients respectively.

324   *E. HYBRID MULTI-SCALE CNN WITH MULTI- ATTENTION ARCHITECTURE*

325   The hybrid model in its basic form, named HMS-MACNN, the frequency multi-scale advance

326   features with attention weights calculated by the Attention MS block 1 are all fused at feature-level.

327   The fused features belong to the advanced features at different time scales .The Attention MS block 2

328   is used to calculate the weights and then fuses them into the decision-level by the proposed weighted

329   soft-voting rule. Finally, the weighted probabilities for each classes are calculated for pattern

330   recognition. The framework of the HMS-MACNN is schematically presented in Figure 3.
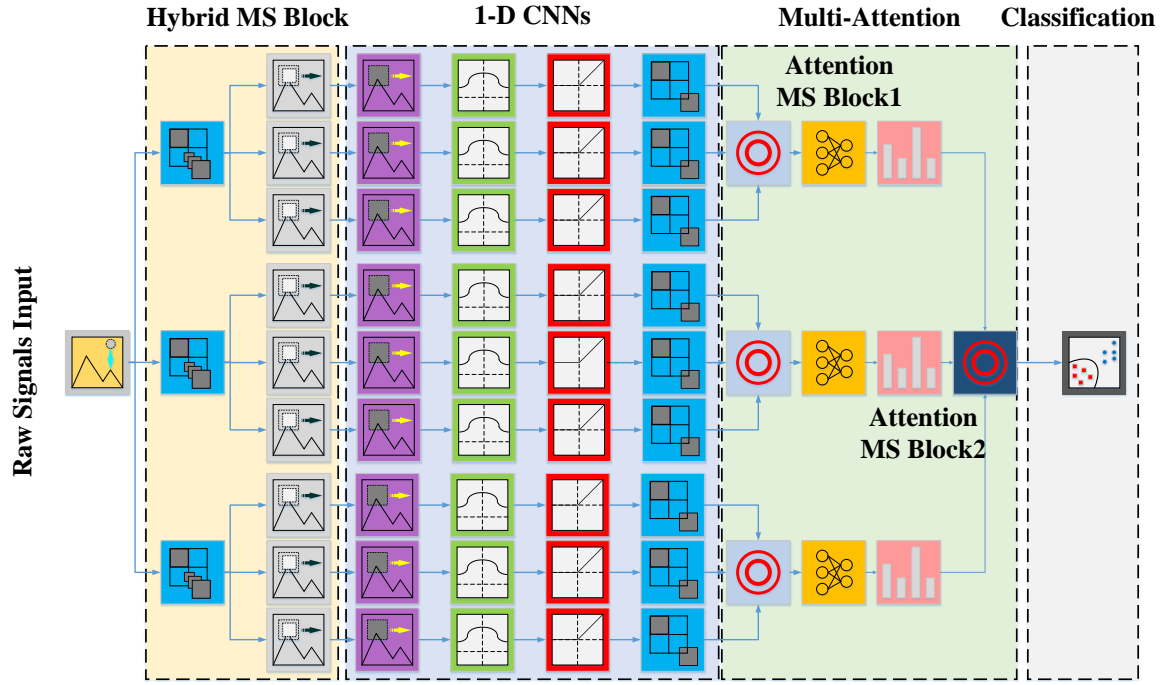

Figure:3 Framework of the HMS-MACNN

331   In Figure 3, the designed 1-D CNNs block, consisting of several convolution kernel, pooling

332   operation, activation function and BN operation, is used to obtain and learn advanced features of the

333   signals from the multi-scale sub-signals. The weighted features calculated by Eq. (12) are fused in

334   decision-level. Both the scale of MS block1 and MS block2 in the hybrid MS block are taken as 3 in

335   this study. The input size of signals is 4096. Details of the HMS-MACNN architecture are presented

336   in Table I. Note that "CNN" consists of convolution, BN, ReLU and Pooling layers.

Table I: Details of the HMS-MACNN model

No	Layer Name Output size (learnables)	Kernels size /stride Filter number	No	Layer Name Output size (learnables)	Kernels size /stride Filter number
1	Input Layer 4096 (-)	-	2	MS Block 1 4096-3 (-)	(S = 1,2,3)
3	MS Block 2 820-9-16	[128]/[5] 16	4	BN+ReLU+Pool 400-9-16	[3]/[2]

	(2048)	(D = 16,32,64)			
5	CNN 1 203-9-32 (1536)	[3]/[1] 32 [3]/[2]	6	CNN 2 100-9-64 (6144)	[3]/[1] 64 [3]/[2]
7	Conv+BN 98-9-128 (24576)	[3]/[1] 128	8	Attention 1 98-3-128	-
9	Fully-Connected (C×37632×3)	-	10	Attention 2 (Classes×3)	-

337   The fault diagnosis framework is built on the following three steps:
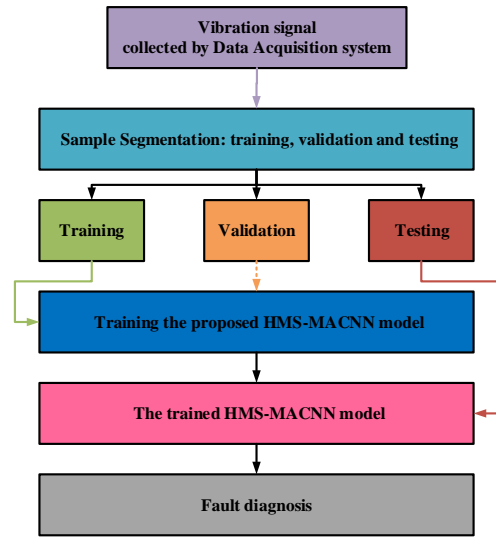

Figure 4：Diagnosis flowchart

338   *Step 1*: Vibration data from healthy and different operating conditions of a gearbox are collected

339   using a data acquisition system. This is followed by segmentation of the signals into smaller segments

340   for training, validation and testing of the model.

341   *Step 2*: developing of end-to-end fault diagnosis system using the training samples obtained from

342   the HMS-MACNN model that were extracted from the raw vibration signals. This step is equipped

343   with an offline training capability. Parameters of the HMS-MACNN model are obtained to prepare for

344   fault diagnosis of the test gearbox following offline training of the input.

345   *Step 3*: In this step, testing samples are transferred to the trained HMS-MACNN model for direct

346   diagnosis of the gearbox faults under various scenarios.

III.   EXPERIMENTAL DESCRIPTION AND DATA COLLECTION METHOD

In this section, the basic information of the experimental platform and the environment in which the model is examined are introduced. A limited experiment is conducted for the purpose of establishing the credibility of the new method through validation of the results. Two experimental dataset are used in this paper. In one of them, raw vibration signals are obtained from the gearbox (Figure 5(a)) via the drivetrain of the dynamic simulator [33]. In the other dataset, raw vibration signals of bearings acquired by conducting several accelerated degradation experiments are obtained from XI'AN Jiaotong University (XJTU) [34] (Figure 5(b)).

In the gearbox examination, we focused on investigating the two different working conditions in which the loads on the system are set at 20 Hz-0V or 30 Hz-2V. The method used in the study allows for an accurate representation of the health status of the gearbox. Details of bearing and gear types and the respective faults diagnosed are presented in Table II. In the degradation bearing examination, we focused on investigating the diagnosis of both single and mixed faults with degradation. Details of degradation bearings with respective faults are presented in Table III.
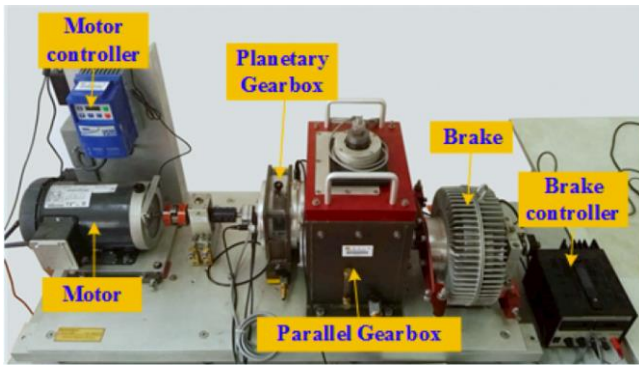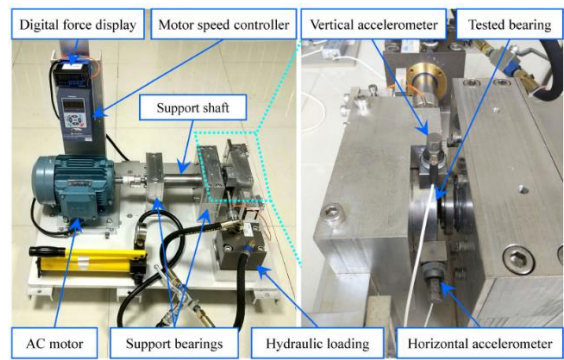

(a) Gearbox rig   (b) XJTU bearing degradation experiment rig

Figure 5：Experimental setup

361   In gearbox fault diagnostic test, experimental dataset from simulations of five different bearing

362   and gear working conditions have been examined in this study. The bearing and gear data comprised

363   of four failure types and one baseline state (healthy condition). Each of the fault types contains 800

364   training samples and 400 validation samples. The dataset used for the training phase of the bearing and

365   gear comprise of 4096 data points obtained from the input vibration signal. To guarantee high fidelity

366   and ensure consistency across the experiment, the size of dataset used in the testing phase is kept the

367   same as the training dataset. Furthermore, bearing and gear failures are combined into a mixed data

368   set containing the four types of failure stated earlier

369   (four bearing failures, and one baseline [healthy]

370   state) to examine the validity of the newly

371   developed method in diagnosing mixed failures. In

372   the degradation bearing fault diagnostic test, only

373   the bearing failure is considered, but the training

374   and test datasets are established over time. This

375   indicates that the bearing damage of the test dataset

376   may be slightly larger than the training dataset, but

377   belongs to the same type of failure category. The

378   schematic diagram of selecting the training set and

379   the test set is shown in Figure 6.
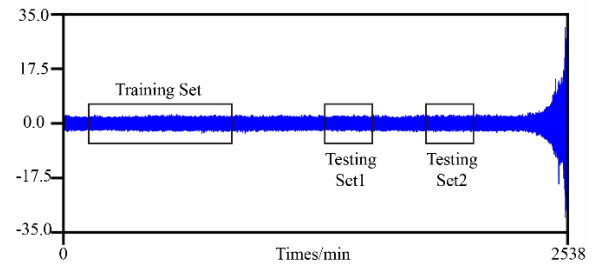
(a) Dataset chosen
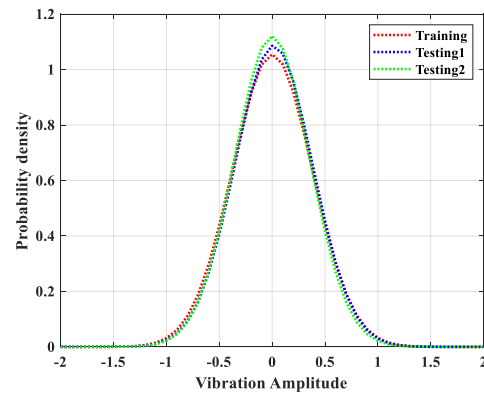
(b) Dataset normal distribution estimation

Figure 6 The dataset segmentation for training and testing

380   Outcome of the examination confirms the superiority of HMS-MACNN model as demonstrated

381   through comparison of the results obtained in this phase of the study with recently published multi-

382 scale diagnosis studies. This includes comparisons with the MSCNN-I [21], MSCNN-II [20], MCCNN

383 [18] and AWMSC [22].

Table II: Gearbox fault types description

Type	Description	Type	Description
Chipped	Gear feet creak	Miss	Missing gear feet
Root	Gear root feet creak	Surface	Gear surface wear
Ball	Ball creak	Outer	Outer race creak
Inner	Inner race creak	Complex	Inner race and outer race creak

384 The precision of HMS-MACNN in accurately diagnosing faults and failure is further enhanced

385 by the implementation of optimization capability. The Adam and Adadelta gradient descent

386 optimization algorithms are respectively used to optimize the CNN-based model and the weighted

387 soft-voting rule [35], in which are a mini-batch processing size of 200 samples is incorporated in the

388 HMS-MACNN framework. The optimization has 30 epochs in the training phase. Consequently, the

389 learning rate of the feature extraction is initialized to 0.001. This was designed to operate without

390 attenuation during the model updating of each step. A 0.5 dropout rate is adopted for the fully

391 connected CNN layer in order to minimize any exposure of the model to the risk of over-fitting [36].

392 For comparisons, the hyper-parameter settings of each multi-scale model are kept the same as those of

393 HMS-MACNN.

Table III: Bearing degradation description

Type	Description
Inner	Only Inner race damage
Outer	Only Outer race damage
Cage	Only Cage race damage
Hybird	Including Inner race and outer race fault

394 Once again, to guarantee the sustenance of model accuracy during feature learning and

395 classification phases, F1 score is used in the comparison and evaluation of the performance of

396   diagnosis model examined in this study. This added capability offers the framework a comprehensive

397   metric for measuring its extrapolation function needed in the model updating phase. A mathematical

398   definition of F1 is presented in Eq. (16).

$$Fl = \frac{2TP}{2TP+FP+FN} \tag{16}$$

399   where TP, FP, TN and FN respectively represent the correctly classified faults as positive samples,

400   wrongly classified faults as positive samples, correctly classified faults as negative and wrongly

401   classified faults as negative.

IV.   RESULTS AND DISCUSSIONS

403   Following the successful testing and validation of the framework, the performance of HMS-

404   MACNN model is evaluated using experimental data obtained from the gearbox test rig. The

405   performance is examined under noisy environment and with variable loading conditions.

406   The comparisons of training and validation accuracies using the proposed HMS-MACNN model

407   and other kinds of multi-scale models examined based on the gearbox dataset are presented in Figure

408   7. The training and test time over 10 random trails between various MS models are given by Table IV.
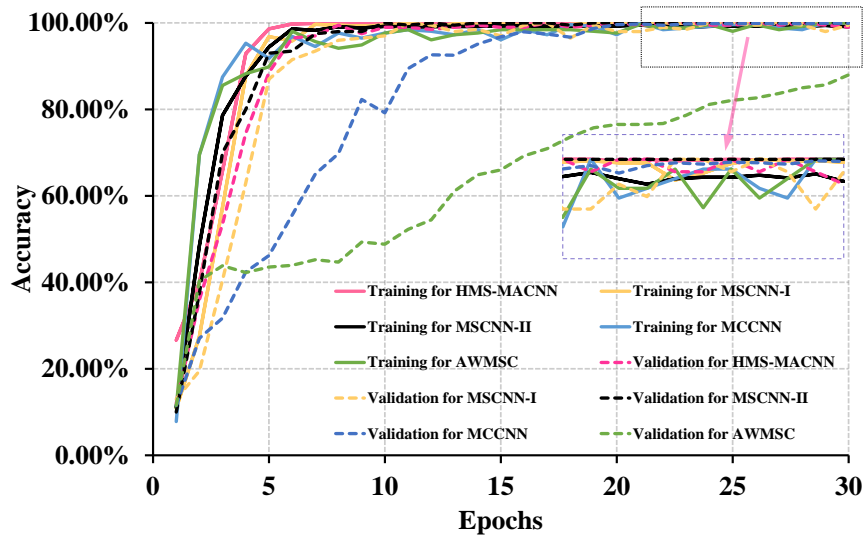
Figure 7: The training and validation accuracy.

409   The training and validation processes of each MS models are presented in Figure 6. Although the

410   proposed HMS-MACNN model's accuracy gradually increases in the first 20 epochs more than those

411   of MSCNN-I and MSCNN-I, the accuracy in the training phase of HMS-MACNN is higher than for

412   other MS models after 20 epochs and equally more stable.

Table IV: COMPARISON BETWEEN VARIOUS MS models FOR OVER 10 RANDOM TRIALS

Methods	Training time (s)	Testing time (s)
HMS-MACNN	397.74±19.61	0.4236±0.0056
MSCNN-I	158.42±6.57	0.3198±0.0055
MSCNN-II	195.27±8.76	0.1352±0.0167
MCCNN	190.13±8.53	0.1609±0.0139
AWMSC	270.10±13.78	0.1464±0.0074

413   Table IV shows that the proposed HMS-MACNN model takes longer time in the training phase

414   due to inherent limitation of computing resources and the process by which the proposed Multi-

415   Attention algorithm handles the dot product of tensors as expected. However, in order to have a

416   realistic basis for comparison with the existing methods, the training process is performed offline and

417   the response time of the proposed HMS-MACNN is completed within a duration of 0.5 seconds only.

418   This slightly exceeds the best duration typically achieved in industrial grade application.

419   In a real industrial application such as wind turbine gearbox that operates in complex operating

420   conditions, the raw vibration signals measured are often drown out by noises. Therefore, the robustness

421   of the HMS-MACNN against noise is examined by injecting additive noise into the signals to

422   reconstruct the raw vibration signals having differences in their signal-to noise ratios (SNR) [37].

423   In this study, the comparison of the robustness of the proposed HMS-MACNN, MSCNN-I,

424   MSCNN-II, MCCNN and AWMSC are examined based on noisy signals with different SNR (-9dB ~

425   9dB). Results from the comparison of the evaluation with the multi-scale models is shown in Figure 8.
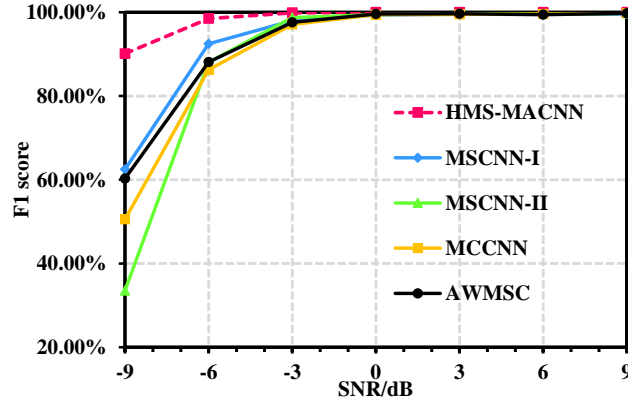
Figure 8: Comparison of anti-noise robustness for model

426   As shown in Figure 8, when the test signals' SNR is equal to -9dB, the HMS-MACNN model

427   produces an average F1 score of nearly 90%, which are respectively at least 27% higher than other

428   kinds of MS models. This implies that the proposed HMS-MACNN model is more capable of working

429   on data within a noisy environment than the other generic models. Because fusion in decision-level is

430   better than feature-level, the proposed soft-voting rule in the Multi-Attention Module avoids any bias

431   in the prediction. Comparison of performances of the MSCNN-I and MSCNN-II shows that, although

432   MSCNN-II uses the dilated convolution to expand the receptive fields and extract multi-scale

433   characteristics from raw signals, the MSCNN-I performs better than MSCNN-II at -9dB. This is

434   because MSCNN-I has an added multi-scale capability for feature extraction layer that is based on

435   multi-scale coarse-grained procedure. Comparison of the robustness of the MSCNN-I and AWMSC

436   model shows that, although the AWMSC model did not use the coarse-grained method to obtain multi-

437   scale features, they have similar robustness when they face the same strong noisy environments. This

438   is because the AWMSC model focuses more on the features extraction channels. The proposed hybrid

439   MS block is more capable of using the multi-scale characteristics extraction than other generic MS

440   models. The contribution of the features at different scales for different fault types is considered by the

441   HMS-MACNN model because it is capable of giving attention to fault features at different scales. This

442 has been demonstrated by the results from the test when the SNR of the test signals increases. The

443 average F1 score of other types of MS models rise quickly and are very close but the HMS-MACNN

444 model still offers the best diagnosis performance. In order to study the misjudgments of fault types by

445 the MS models, the identifications of faults from the MS models at -6dB are shown in Figure 9 using

446 a confusion matrix.

(a) HMS-MACNN

True Labels \ Predicted	Health	Ball	Outer	Inner	Complex	Chipped	Miss	Root	Surface
Health	200	0	0	0	0	0	0	0	0
Ball	0	200	0	0	0	0	0	0	0
Outer	0	0	197	1	0	0	2	0	0
Inner	0	0	0	200	0	0	0	0	0
Complex	0	0	0	0	199	0	1	0	0
Chipped	0	0	0	0	0	200	0	0	0
Miss	0	0	0	0	0	0	200	0	0
Root	0	0	0	0	0	5	0	195	0
Surface	0	0	0	0	0	0	1	0	199

(b) MSCNN-I

True Labels \ Predicted	Health	Ball	Outer	Inner	Complex	Chipped	Miss	Root	Surface
Health	197	0	0	0	1	0	0	0	2
Ball	0	192	0	1	7	0	0	0	0
Outer	0	0	159	30	0	0	1	10	0
Inner	0	0	0	192	1	0	4	2	1
Complex	0	0	0	1	199	0	0	0	0
Chipped	0	0	0	0	0	166	7	27	0
Miss	0	0	0	6	1	0	192	0	1
Root	0	0	0	1	0	3	0	195	1
Surface	3	0	0	5	11	0	1	0	180

(c) MSCNN-II

True Labels \ Predicted	Health	Ball	Outer	Inner	Complex	Chipped	Miss	Root	Surface
Health	182	0	0	0	1	0	3	2	12
Ball	0	184	0	0	0	0	0	0	16
Outer	0	0	184	0	0	15	0	1	0
Inner	4	11	14	116	2	0	33	2	18
Complex	1	0	0	0	182	0	8	0	9
Chipped	0	0	0	0	0	197	1	2	0
Miss	2	0	1	0	0	1	192	1	3
Root	0	0	0	0	0	17	0	183	0
Surface	1	0	0	0	1	0	4	3	191

(d) MCCNN

True Labels \ Predicted	Health	Ball	Outer	Inner	Complex	Chipped	Miss	Root	Surface
Health	173	0	0	0	4	0	2	15	6
Ball	1	188	1	0	2	2	6	0	0
Outer	0	0	190	0	0	5	1	4	0
Inner	1	7	12	118	24	4	26	7	1
Complex	0	0	0	0	199	0	1	0	0
Chipped	0	0	9	0	0	185	0	6	0
Miss	0	0	7	3	1	0	186	0	3
Root	0	0	3	0	0	44	0	152	1
Surface	3	1	0	1	21	0	8	0	166

True Labels \ Predicted	Health	Ball	Outer	Inner	Complex	Chipped	Miss	Root	Surface
Health	185	3	0	0	0	0	0	4	8
Ball	0	200	0	0	0	0	0	0	0
Outer	0	0	194	0	0	2	0	4	0
Inner	0	79	0	71	0	0	45	2	3
Complex	0	1	0	0	193	0	0	0	6
Chipped	0	0	0	0	0	199	0	1	0
Miss	0	9	0	0	0	0	178	0	13
Root	0	0	0	0	0	3	0	196	1
Surface	1	11	0	0	0	0	0	0	188

(e) AWMSC

Figure 9: Comparison through confusion matrix results

447   As shown in Figure 9, the HMS-MACNN model only has a negligible false positive rate. In the

448   case with a -6dB noise, the positive false that exists between Gear feet creak and outer race creak

449   becomes small due to the proposed weighted soft-voting method. The false alarm rates of the other

450   kinds of MS models are much higher, especially for the inner race fault. Identifying the gear root feet

451   creak under a background with large noise using the MCCNN model is difficult. The performance of

452   the proposed HMS-MACNN model stood out better against many generic MS models. The proposed

453   Multi-Attention block added a key function to the HMS-MACNN that plays a critical role in enhancing

454   the extrapolation capability. The extrapolation capability of a CNN-based model in real world

455   application is important. Therefore, the generalization ability of each MS model is examined by the

456   mixed test set with noise, in which the data of 20Hz-0V accounts for 50% and the data of 30Hz-2V

457   accounts for 50%. A comparison of results with those from other MS models are presented in Table V.

TABLE V: COMPARISON WITH KINDS OF MS MODELS IN TERMS OF F1 SCORE FOR EACH FAULT TYPES (%)

Methods	Health	Ball	Outer	Inner	Complex	Chipped	Miss	Root	Surface	Average
HMS-MACNN	99.34±0.0013	**99.47±0.0033**	**99.46±0.0009**	98.65±0.0036	**99.88±0.0006**	**99.39±0.0056**	98.56±**0.0014**	**98.66±0.0012**	97.33±0.0049	**98.97**
MSCNN-I	95.37±0.0077	98.14±0.0054	89.55±0.0110	91.41±0.0076	95.28±0.0052	88.47±0.0116	93.30±0.0496	92.97±0.0092	94.25±0.0067	93.20
MSCNN-II	91.05±0.0078	90.88±0.0113	87.64±0.0071	81.66±0.0047	85.96±0.0064	91.73±0.0069	89.80.±0.0039	90.52±0.0079	88.03±0.0078	88.59
MCCNN	93.14±0.0093	94.00±0.0054	92.88±0.0060	83.28±0.0110	92.01±0.0064	90.52±0.0088	92.20±0.0611	86.56±0.0128	89.87±0.0087	90.50
AWMSC	96.44±0.0035	87.75±0.0047	97.96±0.0076	78.38±0.0087	97.59±0.0054	96.79±0.0047	87.80±0.0078	95.09±0.0076	90.29±0.0076	92.01

458   From Table V, the average F1 score shows that the proposed HMS-MACNN model has an

459   accuracy of 98.87% when the testing environments include variable loads and strong noise. This result

460   is 6% higher than the second-ranked method, which is the MSCNN-I model. The comparisons of the

461   F1 score reveal that the HMS-MACNN model successfully performs classification task for nine cases

462   in working conditions (one healthy, eight type of failures). The proposed model has the highest F1

463   score in identification of six working conditions. The HMS-MACNN model can automatically learn

464 useful fault characteristics from the raw signals on multiple scales without any manual modifications.

465 This highlights its intelligent capability in diagnosing faults. In addition, the HMS-MACNN model is

466 able to obtain richer information due to its HMS block being assigned with different attention to multi-

467 scale characteristics through the multi-attention block. Therefore, one of the obvious advantages of the

468 proposed HMS-MACNN model is the presence of the multi-scale end-to-end fault diagnosis capability.

469 This uniquely distinguishes the method developed in this study from other generic methods currently
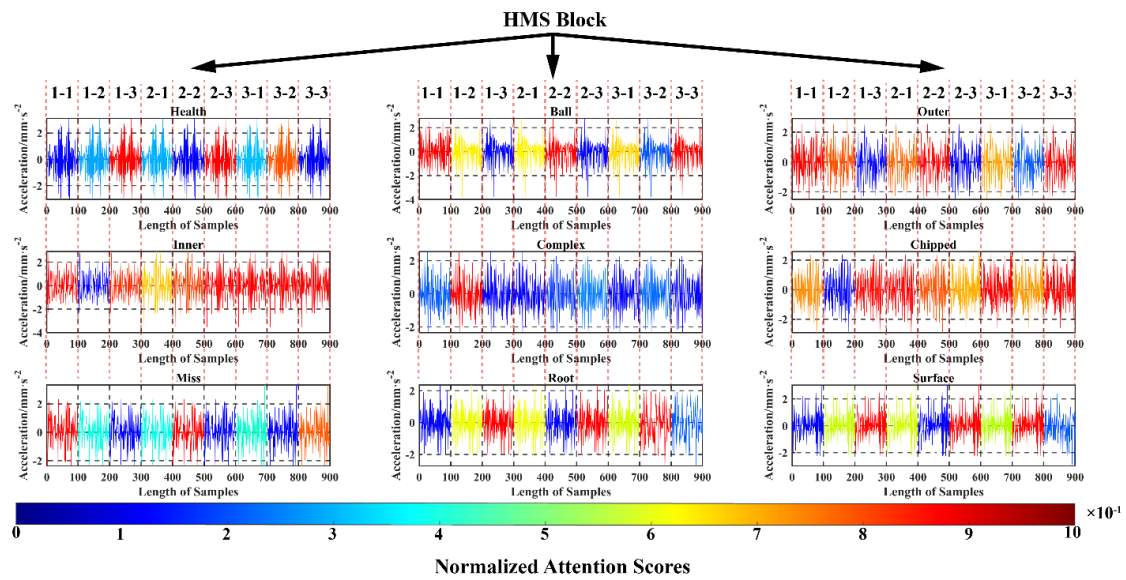
470 being used in the industry.

Figure 10: Scores calculated by multi-attention block 1 for a range of gearbox conditions

471 To further demonstrate the credibility of the proposed HMS-MACNN, the performance of the

472 number of attentions incorporated into the Multi-Attention block for different faults diagnosis are

473 quantified. The attention scores on the multi-time and multi-frequency scale (extracted by HMS block

474 but weighted by Attention 1) for each pattern are expressed in percentage, which are shown in Figure

475 10. '1-1' means the hybrid multi-scale advanced features with 1 time scale and 1 frequency scale.

476 Figure 10 shows that the weights given by the multi-attention block1 that the information

477 collected from HMS block with scale = 1-1 is not sensitive to healthy condition, gear surface wear and
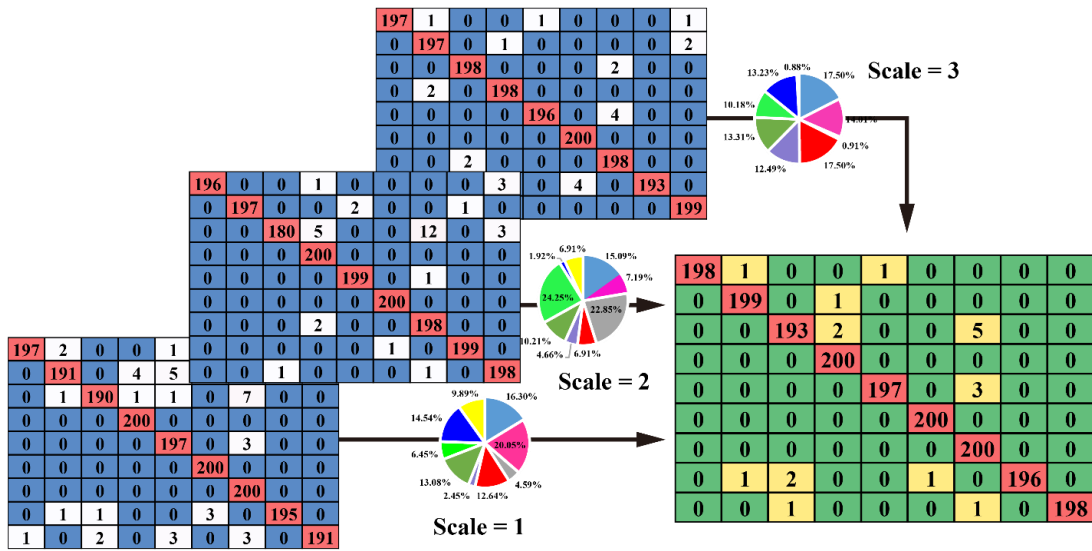
478 gear root creak. The information collected by the HMS block with scale = 1-3 is more sensitive to the

479 health and gear root creak. Each scale has a different sensitivity to different gearbox conditions, which

480 shows the principle of HMS block with multi-attention module to improve the performance of HMS-

481 MACNN.

482   To further demonstrate the credibility of the proposed HMS-MACNN, the attention scores of

483 weighted self-voting procedure and the confusion matrix of classifications are shown in Figure 11.

Figure 11: Mechanism of weighted soft-voting rule in Multi-Attention

484   As shown in Figure 11, scale 1 to scale 3 and final diagnosis results are visualized through the

485 confusion matrix. When the advanced features correspond to scale 1 and scale 2 facing the outer ring

486 fault, the false alarm rate is higher, but scale 3 can recognize the outer race fault better. The false alarm

487 rate in final decision, facing the outer ring fault detection, reduces significantly due to attention put on

488 fusion in the decision level through the proposed weighted soft-voting method.

489   To further confirm the superiority of the proposed weighted soft-voting in the Multi-Attention

490 module, a comparative assessment based on simulations under large noise scenario with the proposed

491 weighted soft-voting and traditional soft-voting is examined as shown as Figure 12.

Average F1 Score = 85.03% (Soft-voting)

Average F1 Score =90.71% (Weighted Soft-voting)

Figure 12: Comparison between traditional soft-voting and the proposed weighted soft-voting

492   As shown in Figure 12, the proposed weighted soft-voting has an average increase of 5% in F1

493   score in comparison with traditional soft-voting. Based on the confusion matrix, weighted soft-voting

494   can significantly improve the precision of gear conditions prediction. This further demonstrates the

495   superiority (in terms of efficiency and performance) of the weighted soft-voting rule over a traditional

496   soft-voting. The false positive rates in faults identification are reduced when weighted soft-voting rule

497   is used, further proving its meaningful contribution over traditional soft-voting.

498   Structural fatigue or improper installation can cause damage to the mechanical structure, but the

499   development of the damage is usually not sudden. Therefore, the model needs to consider the slow

500   changes or evolution of the damage to ensure that the fault can still be identified following any slightest

501   change in material or damage characteristics. Consequently, the degradation test is conducted to prove

502   the extrapolation capability and reliability of the proposed HMS-MACNN model. The results of

503   degradation examination are shown in Figure 13.

	Inner	Cage	Outer	Hybrid
Inner	**175**	**25**	**0**	**0**
Cage	**36**	**157**	**0**	**7**
Outer	**0**	**0**	**194**	**6**
Hybrid	**0**	**1**	**0**	**199**
	Inner	*Cage*	*Outer*	*Hybrid*

	Inner	Cage	Outer	Hybrid
Inner	**152**	**48**	**0**	**0**
Cage	**22**	**160**	**4**	**14**
Outer	**0**	**1**	**171**	**28**
Hybrid	**0**	**0**	**0**	**200**
	Inner	*Cage*	*Outer*	*Hybrid*

(a) Examined by Testing set 1 under -9dB

Average F1 Score =90.50%

(b) Examined by Testing set 2 under -9dB

Average F1 Score =85.31%

Figure 13: Confusion matrix of the test results of HMS-MACNN model examined under different testing set

504   As shown in Figure 13, the difference between test data 1 and test data 2 is the change in the

505   degree of damage, resulting from the position of the data collection system. The change of the degree

506   of damage will lead to different forms of mechanical vibration, which ultimately affects the data

507   distribution. When using test data 2 to examine the extrapolation of the HMS-MACNN model, its F1

508   average value is 85.31%, which is 5% lower than Test1's. The reason for this difference is the manner

509   in which samples were collected, with Test2 samples obtained well after training dataset used in Test1

510   (Figure 6a).

V. CONCLUSION

512   This study focused on solving the existing problems in fault diagnosis methods for multi-scale

513   systems by developing a framework that is capable of using raw vibration signals from gearbox. A

514   Hybrid Multi-Scale CNN with Multi-Attention (HMS-MACNN) framework for intelligent fault

515   diagnosis of systems such as the gearbox under various operating conditions and different health states

516   is proposed.

517   The effectiveness of the model is verified via simulations with a gearbox's experimental dataset.

518   The results confirm that HMS-MACNN is more capable of extrapolating faults from systems operating

519   in a complex environment than the existing multi-scale CNN models considered in this study. Addition

520   of interference in the process of multi-scale time feature extraction can enhance the robustness of the

521   model. The effectiveness of the improved multi-scale block have been have verified using anti-noise

522   tests. The contribution of feature extractions with different scales are calculated using the multi-

523   attention block. The self-attention in multi-attention block 1 effectively gives different high-level

524   feature weights. The weighted soft-voting method in the multi-attention blocks effectively corrects the

525   posterior probability of different scales for pattern recognition of machine conditions, which ultimately

526   reduces the false alarm rates of diagnosis. Therefore, this study addresses the shortcomings of multi-

527   scale fault models developed based on generic CNN models and enhances its efficiency and reliability.

CRediT authorship contribution statement

Zifei Xu: Conceptualization, Methodology, Investigation, Software, Validation, Data curation, Writing – original draft. **Musa Bashir:** Conceptualization, Methodology, Investigation, Resources, Data curation, Supervision, Writing – review & editing, Funding acquisition. **Wanfu Zhang:** Methodology, Writing – original draft, Writing – review & editing. **Yang Yang:** Investigation, Writing – review & editing, Supervision, Funding acquisition, Project administration. **Xinyu Wang:** Conceptualization, Formal analysis. **Chun Li:** Funding acquisition, Supervision.

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