# **Examplement Education**<br> **Enhanced Fault Diagnosis of Vertical Friction Torque Using<br>
Improved VGG-CNN Network<br>
Xiangjun Du<sup>1+</sup>, Ling Yu<sup>2</sup><br>
<sup>1</sup>School of Mechanical Engineering, Tiangong University, Tianjin, China** *Industry Science and Engineering Vol. 1 No. 7, 2024*<br> **It Diagnosis of Vertical Friction Torque Using<br>
<b>Improved VGG-CNN Network**<br>
Xiangjun Du<sup>1,\*</sup>, Ling Yu<sup>2</sup><br> *Iechanical Engineering, Tiangong University, Tianjin, China Industry Science and Engineering Vol. 1 No. 7, 20***<br>
<b>NOSIS Of Vertical Friction Torque Using**<br> **Xiangjun Du<sup>1\*</sup>, Ling Yu<sup>2</sup><br>** *Engineering, Tiangong University, Tianjin, China***<br>** *Xiangjun Du<sup>1\*</sup>, Ling Yu<sup>2</sup><br>
<i>Procational 11*<br> **11**<br> **11**<br> **11**<br> **11**<br> **12**<br> **14**<br> *2Zoontonal Technical Colleges College; Tianjin, China***<br>** *2Tianjin Light Industry Vocational Technical College; Tianjin, China***<br>** *<sup>2</sup>T Findustry Science and Engineering Vol. 1 No.*<br> **Austry Science and Engineering Vol. 1 No.**<br> **Corresponding Author.**<br> *Corresponding Author.*<br> *Corresponding Author.*<br> **Solutional Technical College; Tianjin, China**<br>
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<sup>1</sup>School of Mechanical Engineering, Tiangong University, <sup>2</sup><br>
<sup>2</sup>Tianjin Light Industry Vocational Technical College; Financed Fault Diagnosis of Vertical Friction**<br> **follow and the URG-CNN Network**<br> *Siangjun Du<sup>1,\*</sup>, Ling Yu<sup>2</sup><br>
<sup>1</sup>School of Mechanical Engineering, Tiangong University, Tian<br>
<sup>2</sup>Tianjin Light Industry Vocational Technic* **The Endine Consumer School of Mechanical School VGG-CNN Network**<br> **Thermography (IRT)**<br> *Theodof Mechanical Engineering, Tiangong University, Tianjin, Changong <sup>2</sup>Tianjin Light Industry Vocational Technical College; Tianj* **diagnostic rates of friction to the friction of Mechanical Engineering, Tiangong University, Tianjin, Chinemain of** *College: Tianjin Cight Industry Vocational Technical College: Tianjin, Chinemain in the <i>Corresponding Au* **upproved vCG-CTTT TVCCWTA**<br>
Value of Mechanical Engineering, Tiangong University, Tian<br>
<sup>2</sup>Tianjin Light Industry Vocational Technical College; Tianjin<br>
\*Corresponding Author.<br> **Abstract: This paper presents a CNN-based Faultion School of Mechanical Engineering, Tiangong University, Tianjin,**<br>
<sup>1</sup> *School of Mechanical Engineering, Tiangong University, Tianjin, C<br>
<sup>2</sup> <i>Tianjin Light Industry Vocational Technical College; Tianjin, C<br> fau* **Example 1. Example 1. We all the statistical College:** Transferrencent *College:* Transferrencent *College:* Transferrencent *College:* Transferrencent *College:* Transferrencent **Abstract:** This paper presents a CNN**imaging the study of Mechanical Engineering, Tangong University, Tianjin, C**<br>
<sup>2</sup>Tianjin Light Industry Vocational Technical College; Tianjin, C<br>
\*Corresponding Author.<br> **imaging the study of the study of the study of the Example of the six school of Mechanical Engineering, Lungong Conversity, Lungong 2 Tiany \* Corresponding Author.**<br> **Abstract: This paper presents a CNN-based** bearing torque is **fault diagnosis method utilizing Infrared** Friangin Ligni mausry vocational recentral College; Frany<br>
\*Corresponding Author.<br> **Abstract:** This paper presents a CNN-based bearing torque is<br>
fault diagnosis method utilizing Infrared demonstrates that ver<br>
diagnostic Corresponaing Author.<br> **Abstract:** This paper presents a CNN-based<br>
fault diagnosis method utilizing Infrared<br>
demonstrates that vertical Thermography (IRT) to improve the low<br>
torque bearing senhance<br>
diagnostic rates of Abstract: This paper presents a CNN-based<br>fault diagnosis method utilizing Infrared<br>Thermography (IRT) to improve the low<br>torque bearings e<br>diagnostic rates of friction torque faults in<br>allowing them to be<br>upright placemen Abstract: This paper presents a CNN-based<br>fault diagnosis method utilizing Infrared<br>fault diagnosic rates of friction torque faults in<br>diagnostic rates of friction torque faults in<br>allowing them to bettee<br>upright placement **Example 19 Allert Constant Const** Tauti diagnosis method utilizing infrared demonstrates that the diagnosit discreption diagnosite rate of diagnosite rates of friction torque faults in a lowing them to upright placements and to address bearing torques, whi **Thermography (IKT)** to improve the tow the coalings emances load<br>
diagnostic rates of friction torque balls in a lowing them to better withstand<br> **quright placements and to address bearing** torques, while also reducing ax **attention** and the datents and the datents and the and the summing the service in a test bench. Employing non-<br> **atults in a test bench.** Employing non-<br> **atternative, non-contact infrared thermal** Additionally, vertice<br> **compared accuracy and the and the control of the station and performance evaluation and performance evaluation** and performance evaluation and the classification and the control of the control of the control of the perfor **The set of the set of t nestructive, non-contact infrared thermal** Additionality, vertical conductriate and minimizion and minimizion and animaged outer ring, defective Current fault diagnosis remarble, insufficient lubrication, and based, stati maging eccinology, the study conducts tests<br>
across is the marginal and<br>
inner ring, damaged outer ring, defective<br>
inner ring, damaged outer ring, defective<br>
Current fault diag<br>
marble, insufficient lubrication, and based across six scenarios: uncannaged, damaged<br>
inner ring, damaged onter ring, defective<br>
marble, insufficient lubrication, and based, statistical, and<br>
damaged inner and outer ring bearings.<br>
This article implements a thermal mner ring, damaged outer ring, detective<br>
damaged inner and outer ring bearings.<br>
damaged inner and outer ring bearings.<br>
damaged inner and outer ring bearings.<br>
This article implements a thermal image<br>
offers a non-invasi marbie, insulfied it turncation, and based, statistical, a<br>
diamaged inner and outer ring bearings.<br>
This article implements a thermal image<br>
offers a non-invasive, n<br>
processing technique based on two-<br>
condition monitori **annaged inner and outer ring bearings.** approaches. Initiated included inter-<br> **This article implements a thermal image** offers a non-invasive, non-<br> **processing technique based on two-** condition monitoring, delived<br> **di** This article implements a thermal image<br>
processing technique based on two<br>
dimensional discrete wavelet transform,<br>
and reliability [3]. Tradition<br>
combining VGG Net model with CBAM<br>
diagnosis methods generate<br>
attention processing tecnnique based on two<br>dimensional discrete wavelet transform<br>combining VGG Net model with CBAN<br>attention mechanism to improv<br>classification accuracy while reducin<br>training time. Convolutional neur:<br>networks wer **EXECUTE:** The model with CBAM diagnosis met<br> **Exabsification** mechanism to improve and struggle<br>
classification accuracy while reducing<br> **Convolutional neural** limitations v<br> **Exabsification and performance evaluation**, C **Example 10 Example 10 Example 10 CHATE CONSTRATIGON EXAMPLE TRANGE CONVIDUAL THAT CONVIDUAL CONVIDUAL CONTABUTION**<br> **Fraining time. Convolutional neural** limitations with its<br> **Example the energy dentifiers been e Example the manning time and training** the convolutional neural imitations with<br> **Networks** were then employed for fault capabilities.<br> **Confinition** and performance evaluation,<br> **Common** bearing<br> **Report vector machines.** Training time. Convolutional neural<br>
networks were then employed for fault<br>
classification and performance evaluation,<br>
demonstrating superior results compared to<br>
support vector machines. This approach<br>
effectively identi classification and performance evaluation<br>demonstrating superior results compare<br>support vector machines. This appre<br>effectively identifies bearing torque fa<br>achieving an impressive 99.80% accura<br>classifying faulty bearing

achieving an impressive 99.80% accuracy in<br>
classifying faulty bearings, indicating its<br>
often requires e:<br>
broad applicability.<br>
Keywords: Infrared Thermography;<br>
Evaluation Torque; Convolutional Neural<br>
eliminating the n classifying faulty bearings, indicating its<br>
broad applicability.<br>
Leading to subpar classifica<br>
Keywords: Infrared Thermography;<br>
automatically extract feature<br>
Friction Torque; Convolutional Neural<br>
Neural<br>
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Pr **Examplicability.**<br> **Examplicability.** Friction Torque; Convolutional Neural aliminating extract feat<br> **Examplement Friction Torque; Convolutional Neural** aliminating the need for **r**<br> **Networks;** Support Vector Machines; Surface Convolutional net<br>
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1. Introduction<br>
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Dearings, a **Exerces Searing Convolutional Neural**<br> **Exerces Support Vector Machines;** automatically extract<br> **Friction Torque; Convolutional Neural**<br> **Exerces Exerces**<br> **Exerces Searings**, **Fault Diagnosis**<br> **Exerces Exerces**<br> **Exerc** Friction Torque; Convolutional Neural<br>
Metworks; Support Vector Machines; Previous studies have appliced<br>
imaging for bearing fault Diagnosis<br>
1. Introduction<br>
Bearings, as a key component of friction<br>
election<br>
depending

*y Science and Engineering Vol. 1 No. 7, 2024*<br> **ideal. Friction Torque Using**<br> **NN Network**<br>
Ling Yu<sup>2</sup><br> *pagong University, Tianjin, China*<br> *hnical College; Tianjin, China*<br> *Author.*<br> *Author.*<br>
bearing torque is cruci **The manufacture of Friction Torque Using**<br> **Charge Trive State Constrained SNN Network**<br>
Ling Yu<sup>2</sup><br> *Manical College; Tianjin, China*<br> *Author.*<br> *Author.*<br>
bearing torque is crucial. This study<br>
demonstrates that verti **Tical Friction Torque Using**<br> **Compary Transform Willing Yu<sup>2</sup><br>
Transform University, Tianjin, China<br>** *Author.***<br>
Author.<br>
bearing torque is crucial. This study<br>
demonstrates that vertical placement of friction<br>
torque bea EXECUTE:**<br> **EXECUTE:**<br> **EXEC THIN INEUWOFK**<br>
Ling Yu<sup>2</sup><br>
rigong University, Tianjin, China<br>
hnical College; Tianjin, China<br>
Author.<br>
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demonstrates that vertical placement of friction<br>
torque bearings enhances lo Ling Yu<sup>2</sup><br> *Magong University, Tianjin, China*<br> *Author.*<br> *Author.*<br> *Author.*<br> **bearing** torque is crucial. This study<br>
demonstrates that vertical placement of friction<br>
torque bearings enhances load capacity,<br>
allowing Ling Yu<sup>2</sup><br>
Higheral College; Tianjin, China<br>
Antical College; Tianjin, China<br>
Author.<br>
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ingong University, Tianjin, China<br>
hinical College; Tianjin, China<br>
Author.<br>
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al maintain College; Tianjin, China<br>
thical College; Tianjin, China<br>
Author.<br>
bearing torque is crucial. This study<br>
demonstrates that vertical placement of friction<br>
torque bearings enhances load capacity,<br>
allowing them to *Author.*<br> *Author.*<br> *Author.*<br> **bearing** torque is crucial. This study<br>
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torque bearings enhances load capacity,<br>
allowing them to better withstand forces and<br>
torques, wh Author.<br>
bearing torque is crucial. This study<br>
demonstrates that vertical placement of friction<br>
torque bearings enhances load capacity,<br>
allowing them to better withstand forces and<br>
torques, while also reducing axial lo bearing torque is crucial. This study<br>demonstrates that vertical placement of friction<br>torque bearings enhances load capacity,<br>allowing them to better withstand forces and<br>torques, while also reducing axial load, which<br>ben bearing torque is crucial. This study<br>demonstrates that vertical placement of friction<br>torque bearings enhances load capacity,<br>allowing them to better withstand forces and<br>torques, while also reducing axial load, which<br>ben

bearing torque is crucial. This study<br>demonstrates that vertical placement of friction<br>torque bearings enhances load capacity,<br>allowing them to better withstand forces and<br>torques, while also reducing axial load, which<br>ben demonstrates that vertical placement of friction<br>torque bearings enhances load capacity,<br>allowing them to better withstand forces and<br>torques, while also reducing axial load, which<br>benefits lifespan and performance.<br>Additi torque bearings enhances load capacity,<br>allowing them to better withstand forces and<br>torques, while also reducing axial load, which<br>benefits lifespan and performance.<br>Additionally, vertical orientation improves<br>lubrication allowing them to better withstand forces and<br>torques, while also reducing axial load, which<br>benefits lifespan and performance.<br>Additionally, vertical orientation improves<br>lubrication and minimizes wear, as gravity<br>helps ma torques, while also reducing axial load, which<br>benefits lifespan and performance.<br>Additionally, vertical orientation improves<br>lubrication and minimizes wear, as gravity<br>helps maintain stability.<br>Current fault diagnosis met benefits litespan and performance.<br>
Additionally, vertical orientation improves<br>
lubrication and minimizes wear, as gravity<br>
helps maintain stability.<br>
Current fault diagnosis methods include rule-<br>
based, statistical, and capabilities. Iubrication and minimizes wear, as gravity<br>helps maintain stability.<br>Current fault diagnosis methods include rule-<br>based, statistical, and physical model<br>approaches. Infrared thermal imaging (IRT)<br>offers a non-invasive, no helps maintain stability.<br>Current fault diagnosis methods include rule-<br>based, statistical, and physical model<br>approaches. Infrared thermal imaging (IRT)<br>offers a non-invasive, non-contact solution for<br>condition monitoring Current fault diagnosis methods include rule-<br>based, statistical, and physical model<br>approaches. Infrared thermal imaging (IRT)<br>offers a non-invasive, non-contact solution for<br>condition monitoring, delivering high accuracy based, statistical, and physical model<br>approaches. Infrared thermal imaging (IRT)<br>offers a non-invasive, non-contact solution for<br>condition monitoring, delivering high accuracy<br>and reliability [3]. Traditional mechanical f

demonstrating superior results compared to algorithms include m<br>
support vector machines. This approach methods such as superfectively identifies bearing torque faults,<br>
achieving an impressive 99.80% accuracy in eural net support vector machines. This approach<br>
effectively identifies bearing torque faults,<br>
classifying faulty bearings, indicating its<br>
classifying faulty bearings, indicating its<br>
classifying faulty bearings, indicating its<br> effectively identifies bearing torque faults, (SVM), k-nearest neight<br>
achieving an impressive 99.80% accuracy in neural networks (ANN)<br>
classifying faulty bearings, indicating its often requires extensive<br>
broad applicabi approaches. Infrared thermal imaging (IRT)<br>offers a non-invasive, non-contact solution for<br>condition monitoring, delivering high accuracy<br>and reliability [3]. Traditional mechanical fault<br>diagnosis methods generate conside offers a non-invasive, non-contact solution for<br>condition monitoring, delivering high accuracy<br>and reliability [3]. Traditional mechanical fault<br>diagnosis methods generate considerable noise<br>and struggle to detect issues l condition monitoring, delivering high accuracy<br>and reliability [3]. Traditional mechanical fault<br>diagnosis methods generate considerable noise<br>and struggle to detect issues like lubricant<br>deficiency. In contrast, IRT overc and reliability [3]. Traditional mechanical fault<br>diagnosis methods generate considerable noise<br>and struggle to detect issues like lubricant<br>deficiency. In contrast, IRT overcomes these<br>limitations with its rapid, non-dest diagnosis methods generate considerable noise<br>and struggle to detect issues like lubricant<br>deficiency. In contrast, IRT overcomes these<br>limitations with its rapid, non-destructive<br>capabilities.<br>Common bearing fault classif and struggle to detect issues like lubricant<br>deficiency. In contrast, IRT overcomes these<br>limitations with its rapid, non-destructive<br>capabilities.<br>Common bearing fault classification<br>algorithms include machine learning (M deficiency. In contrast, IRT overcomes these<br>
limitations with its rapid, non-destructive<br>
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Common bearing fault classification<br>
algorithms include machine learning (ML)<br>
methods such as support vector machin Imitations with its rapid, non-destructive<br>capabilities.<br>Common bearing fault classification<br>algorithms include machine learning (ML)<br>methods such as support vector machines<br>(SVM), k-nearest neighbors, and artificial<br>neura capabilities.<br>Common bearing fault classification<br>algorithms include machine learning (ML)<br>methods such as support vector machines<br>(SVM), k-nearest neighbors, and artificial<br>neural networks (ANN) [4]. However, ML<br>often req Common bearing fault classification<br>algorithms include machine learning (ML)<br>methods such as support vector machines<br>(SVM), k-nearest neighbors, and artificial<br>neural networks (ANN) [4]. However, ML<br>often requires extensiv algorithms include machine learning (ML)<br>methods such as support vector machines<br>(SVM), k-nearest neighbors, and artificial<br>neural networks (ANN) [4]. However, ML<br>often requires extensive feature extraction,<br>leading to sub methods such as support vector machines<br>(SVM), k-nearest neighbors, and artificial<br>neural networks (ANN) [4]. However, ML<br>often requires extensive feature extraction,<br>leading to subpar classification results. Deep<br>convolut (SVM), k-nearest neighbors, and artificial<br>neural networks (ANN) [4]. However, ML<br>often requires extensive feature extraction,<br>leading to subpar classification results. Deep<br>convolutional networks (CNN) can<br>automatically e neural networks (ANN) [4]. However, ML<br>often requires extensive feature extraction,<br>leading to subpar classification results. Deep<br>convolutional networks (CNN) can<br>automatically extract features from raw data,<br>eliminating often requires extensive feature extraction,<br>leading to subpar classification results. Deep<br>convolutional networks (CNN) can<br>automatically extract features from raw data,<br>eliminating the need for manual intervention.<br>Previ leading to subpar classification results. Deep<br>convolutional networks (CNN) can<br>automatically extract features from raw data,<br>eliminating the need for manual intervention.<br>Previous studies have applied CNNs to thermal<br>imag convolutional networks (CNN) can<br>automatically extract features from raw data,<br>eliminating the need for manual intervention.<br>Previous studies have applied CNNs to thermal<br>imaging for bearing fault detection, yet issues<br>lik automatically extract teatures from raw data,<br>eliminating the need for manual intervention.<br>Previous studies have applied CNNs to thermal<br>imaging for bearing fault detection, yet issues<br>like slow diagnostic speeds and low

eliminating the need for manual intervention.<br>Previous studies have applied CNNs to thermal<br>imaging for bearing fault detection, yet issues<br>like slow diagnostic speeds and low accuracy<br>persist. Recent advancements have aim

robustness.

**Industry Science and Engineering Vol. 1 No. 7,**<br>for various faulty bearings, showcasing strong<br>robustness.<br>2. Friction Torque Test Bench and Infrared<br>Thermal Imaging<br>The purpose of this study is to diagnose<br>bearing torque **Industry Science and Engineering Vol. 1 No. 7, 2024**<br>
for various faulty bearings, showcasing strong<br>
for various faulty bearings, showcasing strong<br>
the purpose of this study is to diagnose<br>
the purpose of this study is **Computer Science and Engineering Vol. 1 No. 7, 2024**<br>
for various faulty bearings, showcasing strong<br>
for various faulty bearings, showcasing strong<br>  $\begin{array}{ccc}\n\text{2. Friction Torque Test Bench and Infrared} & \text{in this research feature}\\
\text{Thermal Imaging} & \text{designed primarily} & \text{designed primarily}\\
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2. Friction Torque Test Bench and Infrared<br>
Thermal Imaging<br>
2. Friction Torque Test Bench and Industry Science and Engineering Vol. 1 No. 7, 2024<br>
for various faulty bearings, showcasing strong<br>
robustness.<br>
2. Friction Torque Test Bench and Infrared<br>
2. Triction Torque Test Bench and Infrared<br>
2. Triction Torque f Industry Science and Engineering Vol. 1 No. 7, 2024<br>
for various faulty bearings, showcasing strong<br>
Experiments conducted o<br>
colustness.<br>
2. Friction Torque Test Bench and Infrared<br>
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2. Friction Torque Test Bench and Infrared<br>
2. Friction Torque Test Bench and Infrared<br>
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2. Friction Torque Test Bench and Infrared robustness.<br>
2. Friction Torque Test Bench and Infrared<br>
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the purpose of this study is to diagnose<br>
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Thermal Imaging<br>
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The purpose of this study is to diagnose<br>
bearing torque faults using a friction torque starting friction torque<br>
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bearing torestigned primarily the purpose of this study is to diagnose<br>
test bench, simulating various faults that may<br>
components: a mechanical device includes<br>
occur during actu The purpose of this study is to diagnose triction torque, average the bench, simulating various faults using a friction torque starting friction torque. It costs bench, simulating various faults that may concents: a mechan bearing torque faults using a friction torque starting friction torque. It<br>est bench, simulating various faults that may<br>occur during actual bearing operation. This<br>approach allows for real-time monitoring and a control ac test bench, simulating various faults that may<br>
occur during actual bearing operation. This and a contro<br>
approach allows for real-time monitoring and mechanical devi<br>
measurement to detect potential issues [7]. an adjustm



For various faulty bearings, showcasing strong<br>for various faulty bearings, showcasing strong<br>robustness.<br>**2. Friction Torque Test Bench and Infrared**<br>**2. Friction Torque Test Bench and Infrared** in this research feature<br> **2. Friction Torque Test Bench and Infrared**<br> **2. Friction Torque Test Bench and Inf** Experiments conducted on the bearing test<br>Experiments conducted on the bearing test<br>bench involve various high-speed bearings to<br>collect relevant data. The test bench employed<br>in this research features a patented bracket<br>d Experiments conducted on the bearing test<br>Experiments conducted on the bearing test<br>bench involve various high-speed bearings to<br>collect relevant data. The test bench employed<br>in this research features a patented bracket<br>d **Condemic Education**<br>Experiments conducted on the bearing test<br>bench involve various high-speed bearings to<br>collect relevant data. The test bench employed<br>in this research features a patented bracket<br>designed primarily for Experiments conducted on the bearing test<br>Experiments conducted on the bearing test<br>bench involve various high-speed bearings to<br>collect relevant data. The test bench employed<br>in this research features a patented bracket<br>d Experiments conducted on the bearing test<br>Experiments conducted on the bearing test<br>bench involve various high-speed bearings to<br>collect relevant data. The test bench employed<br>in this research features a patented bracket<br>d **follogies and the Control Components: a mecha Subsemier Consisted Friedmin Consistence**<br> **Experiments** conducted on the bearing test<br>
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**Diagnosis**

Figure 1. Experimental Device for Infrared Thermal Imaging Acquisition<br>
This study utilized SKF-manufactured bearings, parameter, varies based on s<br>
with detailed specifications provided in Table 1. the housing material, a Figure 1. Experimental Device for Infrared Thermal Imaging Acquisition in<br>
Diagnosis<br>
This study utilized SKF-manufactured bearings,<br>
with detailed specifications provided in Table 1. the housing material, as well as<br>
A to Figure 1. Experimental Device for Infrared Thermal Imaging Acquisitio<br>
This study utilized SKF-manufactured bearings, parameter, varies based on<br>
with detailed specifications provided in Table 1. the housing material, as Figure 1. Experimental Device for Infrared Thermal Imaging Acquisition in Bias and the transformation of the cross of the cross of the cross of A total of 750 images were captured at three humidity, and temperature differ Figure 1. Experimental Device for Infrared Thermal Imaging Acquaintations This study utilized SKF-manufactured bearings, parameter, varies based with detailed specifications provided in Table 1. the housing material A tota Figure 1. Experimental Device for Infrared Thermal Imaging Acquisition in B<br>
Diagnosis<br>
This study utilized SKF-manufactured bearings, parameter, varies based on surfa<br>
with detailed specifications provided in Table 1.<br>
A Figure 1. Experimental Device for Infrared Thermal Imaging Acquisitio<br>This study utilized SKF-manufactured bearings,<br>This study utilized SKF-manufactured bearings, parameter, varies based with detailed specifications prov **Dia**<br>
This study utilized SKF-manufactured bearings,<br>
with detailed specifications provided in Table 1.<br>
A total of 750 images were captured at three<br>
different speeds: 300 rpm, 600 rpm, and 900<br>
rpm, resulting in 11,250 This study utilized SKF-manutactured bearings, parameter, varies based of the distinction of 750 images were captured at three humidity, and temperate at different speeds: 300 rpm, 600 rpm, and 900 experiment, the distanc with detailed specifications provided in Table 1. the housing material, as well a<br>A total of 750 images were captured at three humidity, and temperature<br>different speeds: 300 rpm, 600 rpm, and 900 experiment, the distance A total of 750 images were captured at three humidity, and temperat different speeds: 300 rpm, 600 rpm, and 900 experiment, the distance images. The imager to the target object has diastaset was divided into three parts,

For the distance for the distance from the thermal imager<br>triangle and the mail imager<br>sisted the housing material, as well as distance, relative<br>humidity, and temperature scale. In this<br>experiment, the distance from the t Final Imaging Acquisition in Bearing Fault<br>
Infinited themal imager<br>
Final Imaging Acquisition in Bearing Fault<br>
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the housing material, as well as distance, relative<br>
h THE TREAT IS IN THE TREAT IS IN THE TREAT IS IN THE ISLAM IS<br>
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parameter, varies based on surface properties of<br>
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humidity, and temperature s The the test stand to capture the from the silulation of the housing material, as well as distance, relative humidity, and temperature scale. In this experiment, the di Infared themal imager<br>
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Figure 2 displays and the figure 2 displays and the figure of the minimal Imager<br>parameter, varies based on surface properties of<br>the housing material, as well as distance, relative<br>humidity, and temperature scale. In this Infiared themal imager<br>
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signaremeter, varies based on surface properties of<br>
the housing material, as well as distance, relative<br>
humidity, and temperature scale. In th Imaging Acquisition in Bearing Fault<br>
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parameter, varies based on surface properties of<br>
the housing material, as well as distance, relative<br>
humidity, and temperature scale. In this<br>
experiment, the distance from **Example 12**<br> **Example 12 sis**<br>parameter, varies based on surface properties of<br>the housing material, as well as distance, relative<br>humidity, and temperature scale. In this<br>experiment, the distance from the thermal<br>imager to the target object was parameter, varies based on surface properties of<br>the housing material, as well as distance, relative<br>humidity, and temperature scale. In this<br>experiment, the distance from the thermal<br>imager to the target object was set at the housing material, as well as distance, relative<br>humidity, and temperature scale. In this<br>experiment, the distance from the thermal<br>imager to the target object was set at 1.5 meters<br>to ensure high-quality image resoluti humdity, and temperature scale. In this experiment, the distance from the thermal imager to the target object was set at 1.5 meters to ensure high-quality image resolution [11]. The test bench was initially operated for tw





## **Bearing**

and Solution Priorius Selection (a) Inner Ring Loss (b) Outer Ring Loss (c) Lack of Lubrication (d) Inner Lack of Lubrication (e) Marble Defect (f) Loss<br>
isolate high and low isolate high and low isolate high and low isola The Contrast, the CNN-based dignorisation of the main experiment and the distribution of the CNN-based method for the CNN-based method requires are contrasted in the CNN-based method requires are previously and solution of (d)<br>
Figure 3 Raw Thermal Images of Bearings Captured at 600<br>
(a) Inner Ring Loss (b) Outer Ring Loss (c) Lack of Lubrication (d) Inner a<br>
Lack of Lubrication (e) Marble Defect (f) Loss<br>
siolate high and low frequency<br>
S. Figure 3 Raw Thermal Images of Bearings Captured at 600rpm<br>
Figure 3 Raw Thermal Images of Bearings Captured at 600rpm<br>
Lack of Lubrication (e) Marble Defect (f) Loss<br>
isolate high and low frequence<br>
3. Diagnosis of Faults Figure 3 Raw Thermal Images of Bearings Captured at<br>
Lack of Lubrication (e) Marble Defect (f) Loss<br>
3. Diagnosis of Faults in Friction Torque high-pass and low-pa<br>
3. Diagnosis of Faults in Friction Torque high-pass and (a) Inner Ring Loss (b) Outer Ring Loss (c) Lack of Lubrication (d) Inner a<br>
Lack of Lubrication (e) Marble Defect (f) Loss<br>
isolate high and low-pass<br>
Bearing<br>
The method for diagnosing bearing faults using<br>
The method f Lack of Lubrication (e) M<br>
3. Diagnosis of Faults in Friction Torque<br>
Bearing<br>
The method for diagnosing bearing faults using<br>
CNN and SVM is outlined as follows. Initially,<br>
the SVM approach involves a feature extraction<br> **Example 18**<br>The method for diagnosing bearing faults using<br>CNN and SVM is outlined as follows. Initially,<br>the SVM approach involves a feature extraction<br>and selection process specific to torque bearings.<br>In contrast, the The method for diagnosing bearing faults using<br>
CNN and SVM is outlined as follows. Initially, high-frequency detail coe<br>
the SVM approach involves a feature extraction<br>
and selection process specific to torque bearings.<br> CNN and SVM is outlined as follows. Initially, high-frequency detail coeffic<br>the SVM approach involves a feature extraction<br>low-frequency detail coeffic<br>and selection process specific to torque bearings. frequency approxi

preprocessing and conversion of thermal images<br>
for input into the CNN. Figure 4 illustrates a<br>
concentrated in the<br>
schematic of the proposed diagnostic framework and LH) and low-<br>
that integrates both CNN and SVM for be for input into the CNN. Figure 4 illustrates a concentrated in the detail coef<br>
schematic of the proposed diagnostic framework and LH) and low-frequency c<br>
that integrates both CNN and SVM for bearing in the approximation

**3. Dragnosis of Faults in Friction Torque** ingn-pass and tow-pass interest<br>
The method for diagnosing bearing faults using<br>  $\Delta$  as a result, four sub-band image<br>
The method for diagnosing bearing faults using<br>  $\Delta$  as a the SVM approach involves a feature extraction<br>and selection process specific to torque bearings.<br>
In contrast, the CNN-based method requires Each sub-band image<br>
preprocessing and conversion of thermal images characteris and selection process specific to torque bearings. Irequency approximation coe<br>
In contrast, the CNN-based method requires Each sub-band image<br>
preprocessing and conversion of thermal images<br>
for input into the CNN. Figur In contrast, the CNN-based method requires Each sub-band image<br>preprocessing and conversion of thermal images characteristics, with high-free<br>for input into the CNN. Figure 4 illustrates a concentrated in the detail coeff France Controllery<br>
Assemble Defect (f) Loss<br>
Signals Captured at 600rpm<br>
(f)<br>
The Defect (f) Loss<br>
isolate high and low frequency components,<br>
high-pass and low-pass filters are applied to<br>
cach data line, followed by 2x **Example 3**<br> **Example 3**<br> **Example 3**<br> **Example 2**<br> **Example Defect (f) Loss**<br> **Starble Example 12**<br> **Example 3**<br> **Example 3**<br> **Example Defect (f) Loss**<br> **Starble Defect (f) Example 18 Controlled ACCO**<br>**(f)**<br>**Bearings Captured at 600rpm**<br>**f** Lubrication (d) Inner and Outer Ring Loss,<br>**farble Defect (f) Loss**<br>isolate high and low frequency components,<br>high-pass and low-pass filters are applie Example 1 (f)<br> **Example 2** (f)<br> **Example Defect (f) Loss**<br> **Example 1** and low-pass filters are applied to<br>
each (f)<br> **Bearings Captured at 600rpm**<br> **of Lubrication (d) Inner and Outer Ring Loss,**<br> **Iarble Defect (f) Loss**<br> **isolate high and low frequency components,**<br>
high-pass and low-pass filters are applied to<br>
each data line, f Bearings Captured at 600rpm<br>of Lubrication (d) Inner and Outer Ring Loss,<br>farble Defect (f) Loss<br>isolate high and low frequency components,<br>high-pass and low-pass filters are applied to<br>each data line, followed by 2x down **Bearings Captured at 600rpm**<br>
of Lubrication (d) Inner and Outer Ring Loss,<br> **Iarble Defect (f) Loss**<br>
isolate high and low-frequency components,<br>
high-pass and low-pass filters are applied to<br>
each data line, followed b In Furthermology and Duter Ring Loss,<br> **Starble Defect (f) Loss**<br>
isolate high and low frequency components,<br>
high-pass and low-pass filters are applied to<br>
each data line, followed by 2x downsampling.<br>
As a result, four **Iarble Defect (f) Loss**<br>isolate high and low frequency components,<br>high-pass and low-pass filters are applied to<br>each data line, followed by 2x downsampling.<br>As a result, four sub-band images are generated:<br>high-frequenc isolate high and low frequency components,<br>high-pass and low-pass filters are applied to<br>each data line, followed by 2x downsampling.<br>As a result, four sub-band images are generated:<br>high-frequency detail coefficients (HH high-pass and low-pass litters are applied to<br>each data line, followed by 2x downsampling.<br>As a result, four sub-band images are generated:<br>high-frequency detail coefficient (LH, HL),<br>low-frequency approximation coefficie Bearings Captured at 600rpm<br> **Shower and Outer Ring Loss,**<br> **Shower and Outer Ring Loss,**<br> **Shower and low frequency components**,<br> **high-pass and low-pass filters are applied to**<br>
each data line, followed by 2x downsampli As a result, four sub-band mages are generated.<br>
high-frequency detail coefficients (HH, HL),<br>
low-frequency approximation coefficient (LL) [14].<br>
Each sub-band mage exhibits unique<br>
characteristics, with high-frequency c mgn-inequency detail coefficient (LH), and low-<br>frequency approximation coefficient (LL) [14].<br>Each sub-band image exhibits unique<br>characteristics, with high-frequency components<br>concentrated in the detail coefficients (H Frequency detail coefficient (L1), and low-<br>frequency approximation coefficient (LL) [14].<br>Each sub-band image exhibits unique<br>characteristics, with high-frequency components<br>concentrated in the detail coefficients (HH, H **Example 10**<br> **Explored at 600rpm**<br>
(f)<br> **Captured band band in the capture of the cap** Continued at 600rpm<br>
(f)<br>
Captured at 600rpm<br>
(f)<br>
Laptured at 600rpm<br>
tion (d) Inner and Outer Ring Loss,<br>
eet (f) Loss<br>
gand low-pass filters are applied to<br>
line, followed by 2x downsampling.<br>
t, four sub-band images a bub-band image exhibits unique<br>existics, with high-frequency components<br>ristics, with high-frequency components<br>ated in the detail coefficients (HH, HL,<br>and low-frequency components found<br>pproximation coefficient (LL). Fu ated in the detail coefficients (HH, HL,<br>and low-frequency components found<br>pproximation coefficient (LL). Further<br>sition of the LL band provides an even<br>tailed sub-band image, as illustrated in<br>. Here  $k = 0$  specifies th *x* **Captured at 600rpm**<br>**cation (d) Inner and Outer Ring Loss,**<br>**befect (1) Loss**<br>**high and low frequency components,**<br>**signal low-pass filters are applied to**<br>**ta line, followed by 2x downsampling.**<br>**quency detail coeff befect (f) Loss**<br>
high and low frequency components,<br>
high and low-pass filters are applied to<br>
ta line, followed by 2x downsampling.<br>
ult, four sub-band images are generated:<br>
quency detail coefficients (HH, HL),<br>
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(f)<br>
and **600rpm**<br>
(f) Inner and Outer Ring Loss,<br>
Loss<br>
d low frequency components,<br>
cow-pass filters are applied to<br>
followed by 2x downsampling.<br>
auth-band images are generated:<br>
detail coefficients (HH, HL),<br>
tet (f)<br> **and 600rpm**<br> **Inner and Outer Ring Loss,**<br>
oss<br>
low frequency components,<br>
v-pass filters are applied to<br>
lowed by 2x downsampling.<br>
lo-band images are generated:<br>
tail coefficients (HH, HL),<br>
ail coefficients (HH, For a coorpin<br>a) Inner and Outer Ring Loss,<br>Loss<br>d low frequency components,<br>cov-pass filters are applied to<br>followed by 2x downsampling.<br>sub-band images are generated:<br>detail coefficients (HH, HL),<br>teial coefficients (HH Inner and Outer Ring Loss,<br>
oss<br>
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low-band images are generated:<br>
the band images are generated:<br>
tail coefficient (LH), and low-<br>
mation coefficient (LL) [14].<br>
i

$$
t_{01}(a,b) = \left[L_x * [L_y * I_0]\right] \downarrow_2 (a,b)
$$
  
:\n
$$
t_{31}(a,b) = \left[H_x * [H_y * I_0]\right] \downarrow_2 (a,b)
$$

## *Industry Science and Engineering Vol. 1 No. 7, 2024*

**Bearings**

	argument	Instructions
	Model number	<b>SKF 7207CD</b>
	<b>Contact Angle</b>	10.583°
	Pitch diameter	38.376 mm
	Number of balls/rows	13
	Line number	$\mathcal{D}_{\mathcal{L}}$
	Sphere diameter	$7.5 \text{ mm}$
" c 15.8		



*Industry Science and Engineering Vol. 1 No. 7, 2024*<br>
Where (\*) and ( $\downarrow$ ) represent the convolution and<br>
downsampling processes, respectively [15].<br>
Here (Lx, Ly) and (Hx, Hy) are low-pass and<br>
high-pass filters.<br>
t fi **Industry Science and Engineering Vol. 1 No. 7, 2024**<br>
Where (\*) and (1) represent the convolution and expressed as.<br>
downsampling processes, respectively [15].<br>
Here (Lx, Ly) and (Hx, Hy) are low-pass and  $t_{low}(a,b) = [L_y * I_o$ *Industry Science and Engineering Vol. 1 No. 7, 2024*<br>
Where (\*) and ( $\downarrow$ ) represent the convolution and<br>
downsampling processes, respectively [15].<br>
Here (Lx, Ly) and (Hx, Hy) are low-pass and<br>
high-pass filters.<br>  $t_{0$ *Industry Science and Engineering Vol. 1 No. 7,*<br>Where (\*) and ( $\downarrow$ ) represent the convolution and<br>downsampling processes, respectively [15].<br>Here (Lx, Ly) and (Hx, Hy) are low-pass and<br>high-pass filters.<br> $t_{01}$  filter

$$
\begin{array}{ll}\n\text{4} & \text{Alcademic Education} \\
\text{expressed as.} \\
Y_{low}(a,b) = \left[L_y * I_o\right] \downarrow_2 (a,b) = \sum_{n=2}^1 I_o(a,n) L_y(a,2b-n) \\
t_{01}(a,b) = \left[L_x * \left[L_y * I_o\right] \downarrow_2\right] \downarrow_2 (a,b) = \sum_{n=2}^1 Y_{low}(n,b) L_x(2a-n,b)\n\end{array} \tag{2}
$$
\nFeature selection using PCA

\nSVM

\nFind the following equation:



**Proposed**



Figure 5. Two-dimensional Discrete Wavelet Transform<br>
Figure 5. Two-dimensional Discrete Wavelet Transform<br>
Transform further refine these features<br>
CBAM CNN<br>
CONVOLUTION PROPERTIES (CNNS) are intigrating overfitting.<br>
CON Figure 5. Two-dimensional Discrete Wavelet Transform<br>
Transform further refine these featured<br>
CBAM CNN<br>
CONVIDIONAL TRANS (CNNS) are the extracted features<br>
multi-layer feedforward architectures that utilize the extracted Figure 5. Two-dimensional Discrete Wavelet Transport Figure 5. Two-dimensional Discrete Wavelet Transport CBAM CNN<br>and fully convolutional neural networks (CNNs) are After several rounds<br>multi-layer feedforward architectur Figure 5. Two-dimensional Discrete Wavelet Transfurt<br>
3.2 Friction Torque Fault Diagnosis of VGG-<br>
CBAM CNN<br>
Convolutional neural networks (CNNs) are mitigating overfitting<br>
Convolutional neural networks (CNNs) are After s Figure 5. Two-dimensional Discrete Wavelet Transform<br>
3.2 Friction Torque Fault Diagnosis of VGG-<br>
CBAM CNN<br>
Convolutional neural networks (CNNs) are After several rounds of convolutional neural networks (CNNs) are After s Figure 5. Two-dimensional Discrete Wavelet Transform<br>
further refine these feature<br>
CBAM CNN<br>
Convolutional neural networks (CNNs) are mitigating overfitting.<br>
Convolutional neural networks (CNNs) are After several rounds

Level-2<br>
Level-2<br>
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DWT<br>
HL of level 2<br>
HL of level<br>
dHere fully<br>
dimensions, thereby accelerating processing and<br>
mitigating overfitting.<br>
After several round Example 1<br>
Level-2<br>
DWT<br>
DWT<br>
Level-2<br>
Level-2<br>
Level-2<br>
Hu of level-2<br>
Hu of level-2<br>
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Thu of level-2<br>
Thu of level-2<br>
Thus for classification tasks and<br>
dimensions, there is connected features are fed into For the structure allows CNNs to employ a<br>structure and the velocity of the structure functions of the structure of the extracted features are fed into the fully<br>the extracted features are fed into the fully<br>the extracted screte Wavelet Transform<br>further refine these features by reducing data<br>dimensions, thereby accelerating processing and<br>mitigating overfitting.<br>After several rounds of convolution and pooling,<br>the extracted features are fe screte Wavelet Transform<br>further refine these features by reducing data<br>dimensions, thereby accelerating processing and<br>mitigating overfitting.<br>After several rounds of convolution and pooling,<br>the extracted features are fe **Exercit Wavelet Transform**<br>
further refine these features by reducing data<br>
dimensions, thereby accelerating processing and<br>
mitigating overfitting.<br>
After several rounds of convolution and pooling,<br>
the extracted feature **Example 18 Section**<br> **Example 18 Section**<br> **Example 18 Sections**<br> **Example 18 Secti Example 18 Example 18 Example 18 Example 18 Example 18 After several rounds of convolution and pooling,** the extracted features are fed into the fully connected layers for classification tasks. This structure allows CNNs

**Andemic Education**<br> **Andemic Education**<br> **Andemic Education**<br> **Andemic Education**<br> **Andemic Validation sets in a 7:3 ratio, ensuring that**<br>
each category in the training set contains 750 dataset is processed using<br>
images **Example 19**<br> **Example 20**<br> **Example 20**<br> **Example 20**<br> **Example 20**<br> **EXEL According Process Contains 750**<br> **EXEL According 20**<br> **EXEL According 20**<br> **EXEL According 20**<br> **EXEL ACCOL**<br> **EXEL ACCOL**<br> **EXEL ACCOL**<br> **EXEL AC Publishing House**<br> **Configured Education**<br> **Configured Education**<br> **Configured Education**<br> **Configured Education Strategory** in the training set contains 750 dataset is proce<br>
images, while the validation set comprises th

**Academic Education**<br> **Convolution Fundishing House**<br> **Convolution**<br> **Co Accidentic Education**<br> **Accidentic Education**<br> **Accidentic Education**<br> **Consequent**<br> **Conseque Probabilishing House** *Industry Science and Engineering*<br>and validation sets in a 7:3 ratio, ensuring that applied to the infrared thermal<br>each category in the training set contains 750 dataset is processed using<br>image **CONTIGENT CONSTRANGED THEORY CONTINUIST THEORY OF PUBLISHING PUBLISHING** PUBLISHING and validation sets in a 7:3 ratio, ensuring that applied to the infrared therm each category in the training set contains 750 dataset i **CONTINUMERT ACCORDITED ACCORDITED ACCORDITED ACCORDITED ACCORDITED AND INTERENT ACCORDITED AND ACCORDITED AND ACCORDITED Accelering Education**<br> **Publishing House** Industry Science and Engineering<br>
and validation sets in a 7:3 ratio, ensuring that applied to the infrared therm<br>
each category in the training set contains 750 dataset is proce **The Publishing House** Industry Science and Engineering V<br>
and validation sets in a 7:3 ratio, ensuring that applied to the infrared thermal<br>
each category in the training set contains 750 dataset is processed using t<br>
im External validation sets in a 7:3 ratio, ensuring that<br>each category in the training set contains 750<br>images, while the validation set comprises the<br>remaining images for each label [16].<br>3.2.1 Convolution Layer in Deep Le e validation set comprises the<br>for each label [16]. This<br>Layer in Deep Learning Models vanisl<br>ayer consists of an array of 2D netword<br>ce multiple feature maps. The<br>non-liorks in conjunction with the Softm<br>to combine the r **Example 13** and 1:3 ratio, ensuring that<br>
an the training set contains 750<br>
the validation set comprises the<br>
as for each label [16]. The asset of an array of 2D<br>
layer consists of an array of 2D<br>
ince multiple feature m remaining images for each label [16]. This normalization step mitig<br>3.2.1 Convolution Layer in Deep Learning Models<br>The convolution layer consists of an array of 2D<br>retworks and enhances their<br>filters that produce multipl 3.2.1 Convolution Layer in Deep Learning Models<br>
The convolution layer consists of an array of 2D<br>
retworks and enhances their<br>
filters that produce multiple feature maps. The<br>
non-linear relationships. A<br>
pooling layer w The convolution layer consists of an array of 2D networks and enhances the filters that produce multiple feature maps. The non-linear relationships.<br>pooling layer works in conjunction with the Softmax activation function

$$
B(e,f) = \sum_{m=0}^{\infty} \sum_{n=0}^{\infty} x(m,n)h(e-m,f-n)
$$
 (3)

filters that produce multiple feature maps. The<br>pooling layer works in conjunction with the<br>convolution fiveloutions while reducing the spatial dispersion, improv<br>convolutions while reducing the spatial dispersion, improv pooling layer works in conjunction with the Softmax activation fi<br>convolution layer to combine the results of local dispersion, improv<br>convolutions while reducing the spatial dispersion, improv<br>denotions of the infrared t convolution layer to combine the results of local<br>
dispersion, improving<br>
convolutions while reducing the spatial<br>
dimensions of the infrared thermal images [17].<br>
The 2D convolution operation can be<br>  $B(e,f) = \sum_{m=0}^{\infty} \sum$ convolutions while reducing the spatial efficiency of the bea<br>dimensions of the infrared thermal images [17].<br>The 2D convolution operation can be  $u =$ <br>represented as:<br> $B(e,f) = \sum_{m=0}^{\infty} \sum_{n=0}^{\infty} x(m,n)h(e-m,f-n)$  (3)  $\sigma^2 = \frac$ dimensions of the infrared thermal images [17].<br>
The 2D convolution operation can be<br>
represented as:<br>  $B(e,f) = \sum_{m=0}^{\infty} \sum_{n=0}^{\infty} x(m,n)h(e-m, f-n)$  (3)  $\sigma^2 = \frac{1}{N}$ <br>
In the convolution process, h denotes the<br>
impulse resp The 2D convolution operation can be  $u = \frac{1}{N} \sum_{i=1}^{N} x_i$ <br>represented as:<br> $B(e,f) = \sum_{m=0}^{\infty} \sum_{i=0}^{\infty} x(m,n)h(e-m,f-n)$  (3)  $\sigma^2 = \frac{1}{N} \sum_{i=1}^{N} (x_i - u_i)$ <br>In the convolution process, h denotes the impulse response, while m represented as:<br>  $B(e,f) = \sum_{m=0}^{\infty} \sum_{n=0}^{\infty} x(m,n)h(e-m,f-n)$  (3)  $\sigma^2 = \frac{1}{N} \sum_{i=1}^N {n \choose i}$ <br>
In the convolution process, h denotes the<br>
impulse response, while m and n represent the<br>
pixel values of the input infrared th

 $B(e,f) = \sum_{m=0}^{\infty} \sum_{n=0}^{\infty} x(m,n)h(e-m,f-n)$  (3)  $\sigma^2 = \frac{1}{N} \sum_{i=1}^{N} (x_i$ <br>
In the convolution process, h denotes the<br>
impulse response, while m and n represent the<br>
pixel values of the input infrared thermal (IRT)<br>
image.  $B(e, f) = \sum_{m=0}^{\infty} x(m,n)h(e-m, f-n)$  (3)  $\sigma = \frac{1}{N} \sum_{i=1}^{\infty} (n, n)h(e-m, f-n)$  (3)  $\sigma = \frac{1}{N} \sum_{i=1}^{\infty} (n, n)h(e-m, f-n)$ <br>
In the convolution process, h denotes the<br>
impulse response, while m and n represent the<br>
pixel values of In the convolution process, h denotes the<br>
impulse response, while m and n represent the<br>
pixel values of the input infrared thermal (IRT)<br>
image. The output pixel values after convolution<br>
are denoted as e and f. The con In the convolution process, h denotes the<br>
impulse response, while m and n represent the<br>
pixel values of the input infrared thermal (IRT)<br>
image. The output pixel values after convolution<br>
are denoted as e and f. The con mpulse response, while m and n represent the<br>
pixel values of the input infrared thermal (IRT)<br>
image. The output pixel values after convolution<br>
are denoted as e and f. The convolution Where  $\mu$  denotes the av<br>
operatio pixel values of the input infrared thermal (IR1)<br>
image. The output pixel values after convolution<br>
are denoted as e and f. The convolution<br>
operation utilizes a sliding window to generate<br>
the output for the subsequent l mage. The output pixel values after convolution<br>operation das e and f. The convolution<br>operation utilizes a sliding window to generate<br>represents the input properties,<br>the output for the subsequent layer [18]. total numbe are denoted as e and f. The convolution Where  $\mu$  denotes the ave<br>operation utilizes a sliding window to generate represents the input prop-<br>the output for the subsequent layer [18]. The activation function in the convol operation utilizes a sliding window to generate<br>
represents the input prop<br>
the output for the subsequent layer [18].<br>
The activation function in the convolutional<br>
stands for the normalized<br>
layer plays a crucial role in the output for the subsequent layer [18]. total number of samples, or s<br>
The activation function in the convolutional stands for the normalized samp<br>
layer plays a crucial role in transforming the output after scaling ki, The activation function in the convolutional<br>
stands for the normalized samp<br>
convolved IRT data by introducing nonlinear<br>
transformations. This enhances feature<br>
transformations. This enhances feature<br>
transformations. T layer plays a crucial role in transforming the<br>
convolved IRT data by introducing nonlinear<br>  $\gamma$  and  $\beta$  are the scaling pair<br>
transformations. This enhances feature<br>
representation, promotes sparsity, and addresses<br>
th convolved IRT data by introducing nonlinear  $\gamma$  and  $\beta$  are the scaling parar<br>transformation, promotes pararity, and addresses<br>the gradient vanishing problem, thereby Where  $x'_i$  indicates input an<br>improving the convolu transformations. This enhances teature  $Z_i^t = f(x_i^t) = \max$ <br>representation, promotes sparsity, and addresses<br>the gradient vanishing problem, thereby Where  $x_i^t$  indicates input and Z<br>improving the convolutional neural networ representation, promotes sparsity, and addresses<br>the gradient vanishing problem, thereby<br>improving the convolutional neural network's<br>performance. Common activation functions between two consecutive com<br>include ReLU, Leak the gradient vanishing problem, thereby Where  $x_i$  indicates input a<br>improving the convolutional neural network's The pooling layer is<br>performance. Common activation functions functions by reducing the<br>include ReLU, Leaky mproving the convolutional neural network's The pooling layer is ty<br>performance. Common activation functions between two consecutive con<br>include ReLU, Sigmoid, Tanh, functions by reducing the si<br>and Softmax. While ReLU is performance. Common activation functions<br>
include ReLU, Eacky ReLU, Sigmoid, Tanh,<br>
and Softmax. While ReLU is straightforward, it<br>
can lead to issues such as neuron death, limiting the size<br>
can lead to issues such as neu multi-class class class contracts and produce the and Softmax. While ReLU is straightforward, it map while maintaining a can lead to issues such as neuron death, limiting the interemaps [19]. Pooling its effectiveness in e and Softmax. While ReLU is straightforward, it<br>
can lead to issues such as neuron death, limiting<br>
its effectiveness in extracting bearing features.<br>
In the maximum pooling<br>
Leaky ReLU helps alleviate neuron death by<br>
intr can lead to issues such as neuron death, limiting<br>
its effectiveness in extracting bearing features.<br>
Leaky ReLU helps alleviate neuron death by<br>
introducing a small slope, but selecting the<br>
appropriate slope can be chall Leaky ReLU helps alleviate neuron death by<br>
introducing a small slope, but selecting the<br>
interducing a small slope, but selecting the<br>
interducing a mapropriate slope can be challenging. Sigmoid<br>
cluster of binary<br>
clust introducing a small slope, but selecting the<br>appropriate slope can be challenging. Sigmoid<br>functions are primarily suited for binary<br>classification, making them less effective for<br>multi-class scenarios like faulty bearings introducing a small slope, but selecting the<br>
appropriate slope can be challenging. Sigmoid<br>
contyput, average pooling con<br>
functions are primarily suited for binary<br>
classification, making them less effective for within appropriate slope can be challenging. Sigmoid output, average pooling contunctions are primarily suited for binary the values, and sum poolin explores of the values, and sum poolin multi-class scenarios like faulty bearin functions are primarily suited for binary<br>classification, making them less effective for within the region.<br>multi-class scenarios like faulty beraings. The and Martentanon Manh function also suffers from gradient Feature chassification, making them less effective for<br>
multi-class scenarios like faulty bearings. The 3.2.3 Spatial Attention Mod<br>
Tanh function also suffers from gradient Feature Representation<br>
vanishing, risking the loss of

## *Industry Science and Engineering Vol. 1 No. 7, 2024*

**Example 19**<br> **Configurer Contains Properties Contains Properties (Publishing House**<br> **Configurer 1998**<br>
and validation sets in a 7:3 ratio, ensuring that applied to the infrared thermal<br>
each category in the training set **Convolution Convolution**<br> **Convolution**<br> Academic Education<br>
Industry Science and Engineering Vol. 1 No. 7, 2024<br>
idation sets in a 7:3 ratio, ensuring that<br>
applied to the infrared thermal imaging data, the<br>
tegory in the training set contains 750 dataset is pr Academic Education<br> **Academic Education**<br> **Academic Education**<br> **Academic Education**<br> **Academy** in the training set contains 750 dataset is processed using the Rel. U linear<br>
s, while the validation set comprises the acti mic Education<br>
Industry Science and Engineering Vol. 1 No. 7, 2024<br>
is ets in a 7:3 ratio, ensuring that<br>
in the training set contains 750<br>
in the training set contains 750<br>
tataset is processed using the ReLU linear<br>
the *try Science and Engineering Vol. 1 No. 7, 2024*<br>applied to the infrared thermal imaging data, the<br>dataset is processed using the ReLU linear<br>activation function, as represented in equation 6.<br>This normalization step mitig *try Science and Engineering Vol. 1 No. 7, 2024*<br>applied to the infrared thermal imaging data, the<br>dataset is processed using the ReLU linear<br>activation function, as represented in equation 6.<br>This normalization step mitig try Science and Engineering Vol. 1 No. 7, 2024<br>applied to the infrared thermal imaging data, the<br>dataset is processed using the ReLU linear<br>activation function, as represented in equation 6.<br>This normalization step mitigat try Science and Engineering Vol. 1 No. 7, 2024<br>applied to the infrared thermal imaging data, the<br>dataset is processed using the ReLU linear<br>activation function, as represented in equation 6.<br>This normalization step mitigat try Science and Engineering Vol. 1 No. 7, 2024<br>applied to the infrared thermal imaging data, the<br>dataset is processed using the ReLU linear<br>activation function, as represented in equation 6.<br>This normalization step mitigat try *Science and Engineering Vol. 1 No. 7, 2024*<br>applied to the infrared thermal imaging data, the<br>dataset is processed using the ReLU linear<br>activation function, as represented in equation 6.<br>This normalization step mitig *try Science and Engineering Vol. 1 No. 7, 2024*<br>applied to the infrared thermal imaging data, the<br>dataset is processed using the ReLU linear<br>activation function, as represented in equation 6.<br>This normalization step miti *try Science and Engineering Vol. 1 No. 7, 2024*<br>applied to the infrared thermal imaging data, the<br>dataset is processed using the ReLU linear<br>activation function, as represented in equation 6.<br>This normalization step miti try Science and Engineering Vol. 1 No. 7, 2024<br>applied to the infrared thermal imaging data, the<br>dataset is processed using the ReLU linear<br>activation function, as represented in equation 6.<br>This normalization step mitiga try Science and Engineering Vol. 1 No. 7, 2024<br>applied to the infrared thermal imaging data, the<br>dataset is processed using the ReLU linear<br>activation function, as represented in equation 6.<br>This normalization step mitiga Engineering *Vol. 1 No. 7, 2024*<br>
Franced thermal imaging data, the<br>
sssed using the ReLU linear<br>
n, as represented in equation 6.<br>
on step mitigates the gradient<br>
ften encountered in deep neural<br>
hances their ability to **eering Vol. 1 No. 7, 2024**<br>thermal imaging data, the<br>using the ReLU linear<br>represented in equation 6.<br>p mitigates the gradient<br>necountered in deep neural<br>s their ability to express<br>ips. Additionally, the<br>netion addresses ing the ReLU linear<br>presented in equation 6.<br>mitigates the gradient<br>buntered in deep neural<br>heir ability to express<br>i. Additionally, the<br>ion addresses gradient<br>the convergence<br>cault diagnosis model.<br> $\sum_{i=1}^{N} x_i$  (4)<br> $\sum$ *x x n x* **<b>***x d* **Engineering Vol. 1 No. 7, 2024**<br>
infrared thermal imaging data, the<br>
coessed using the ReLU linear<br>
tion, as represented in equation 6.<br>
step mitigates the gradient<br>
often encountered in deep neural<br>
enhances their a *Engineering Vol. 1 No. 7, 2024<br>
frared thermal imaging data, the<br>
essed using the ReLU linear<br>
on, as represented in equation 6.<br>
ion step mitigates the gradient<br>
offern encountered in deep neural<br>
nhances their abilit* **eering Vol. 1 No. 7, 2024**<br>
thermal imaging data, the<br>
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s their ability to express<br>
s their ability to express<br>
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frared thermal imaging data, the<br>
frared thermal imaging data, the<br>
sesed using the ReLU linear<br>
on as represented in equation 6.<br>
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frem encountered in dee* and Engineering Vol. 1 No. 7, 2024<br>
the infrared thermal imaging data, the<br>
processed using the ReLU linear<br>
unction, as represented in equation 6.<br>
ulization step mitigates the gradient<br>
sisue often encountered in deep n

$$
u = \frac{1}{N} \sum_{i=1}^{N} x_i
$$
 (4)

$$
\sigma^2 = \frac{1}{N} \sum_{i=1}^{N} (x_i - u_i)^2
$$
 (5)

$$
k_i = \frac{x_i - u}{\sqrt{\sigma^2 + \varepsilon}}
$$
 (6)

$$
y_i = \gamma k_i + \beta \tag{7}
$$

Softmax activation function addresses gradient<br>dispersion, improving the convergence<br>efficiency of the bearing fault diagnosis model.<br> $u = \frac{1}{N} \sum_{i=1}^{N} x_i$  (4)<br> $\sigma^2 = \frac{1}{N} \sum_{i=1}^{N} (x_i - u_i)^2$  (5)<br> $k_i = \frac{x_i - u}{\sqrt{\sigma^2 + \varepsilon$ dispersion, improving the convergence<br>
efficiency of the bearing fault diagnosis model.<br>  $u = \frac{1}{N} \sum_{i=1}^{N} x_i$  (4)<br>  $\sigma^2 = \frac{1}{N} \sum_{i=1}^{N} (x_i - u_i)$  (5)<br>  $k_i = \frac{x_i - u}{\sqrt{\sigma^2 + \varepsilon}}$  (6)<br>  $y_i = \gamma k_i + \beta$  (7)<br>
Where  $\mu$  denotes efficiency of the bearing fault diagnosis model.<br>  $u = \frac{1}{N} \sum_{i=1}^{N} x_i$  (4)<br>  $\sigma^2 = \frac{1}{N} \sum_{i=1}^{N} (x_i - u_i)$  (5)<br>  $k_i = \frac{x_i - u}{\sqrt{\sigma^2 + \varepsilon}}$  (6)<br>  $y_i = \gamma k_i + \beta$  (7)<br>
Where  $\mu$  denotes the average of the sample, xi<br>
represe  $u = \frac{1}{N} \sum_{i=1}^{N} x_i$  (4)<br>  $\sigma^2 = \frac{1}{N} \sum_{i=1}^{N} (x_i - u_i)$  (5)<br>  $k_i = \frac{x_i - u}{\sqrt{\sigma^2 + \varepsilon}}$  (6)<br>  $y_i = \gamma k_i + \beta$  (7)<br>
Where  $\mu$  denotes the average of the sample, xi<br>
represents the input properties, N indicates the<br>
total n  $u = \frac{1}{N} \sum_{i=1}^{N} x_i$  (4)<br>  $\sigma^2 = \frac{1}{N} \sum_{i=1}^{N} (x_i - u_i)^2$  (5)<br>  $k_i = \frac{x_i - u}{\sqrt{\sigma^2 + \varepsilon}}$  (6)<br>
Where  $\mu$  denotes the average of the sample, xi<br>
represents the input properties, N indicates the<br>
total number of samples,  $σ<sup>2</sup> = \frac{1}{N} \sum_{i=1}^{N} (x_i - u_i)^2$  (5)<br>  $k_i = \frac{x_i - u}{\sqrt{\sigma^2 + \varepsilon}}$  (6)<br>  $y_i = \gamma k_i + \beta$  (7)<br>
Where μ denotes the average of the sample, xi<br>
represents the input properties, N indicates the<br>
total number of samples, σ is the *x*<sub>*i*</sub> =  $\frac{x_i - u}{\sqrt{\sigma^2 + \varepsilon}}$  (6)<br>  $y_i = \gamma k_i + \beta$  (7)<br>  $\mu$  denotes the average of the sample, xi<br>
number of samples,  $\sigma$  is the variance, ki<br>
for the normalized sample value, yi is the<br>
after scaling ki,  $\varepsilon$  is a sma (6)<br>
(7)<br>
of the sample, xi<br>
N indicates the<br>
the variance, ki<br>
e value, yi is the<br>
all constant, and<br>
rs.<br>
0,  $x_t^l$ }
(8)<br>
indicates output.<br>
ally positioned<br>
lution layers and<br>
of each feature<br>
that number of

$$
Z_t^l = f\left(x_t^l\right) = \max\left\{0, x_t^l\right\} \tag{8}
$$

Where  $x_t^i$  indicates input and  $Z_t^i$  indicates output.  $k_i = \frac{x_i - u}{\sqrt{\sigma^2 + \varepsilon}}$  (6)<br>  $y_i = \gamma k_i + \beta$  (7)<br>
Where  $\mu$  denotes the average of the sample, xi<br>
represents the input properties, N indicates the<br>
total number of samples,  $\sigma$  is the variance, ki<br>
stands for the normali  $\sqrt{\sigma^2 + \varepsilon}$ <br>  $y_i = \gamma k_i + \beta$  (7)<br>
Where  $\mu$  denotes the average of the sample, xi<br>
represents the input properties, N indicates the<br>
total number of samples,  $\sigma$  is the variance, ki<br>
stands for the normalized sample val  $y_i = \gamma k_i + \beta$  (7)<br>Where  $\mu$  denotes the average of the sample, xi<br>represents the input properties, N indicates the<br>total number of samples, o is the variance, ki<br>stands for the normalized sample value, yi is the<br>output af Where  $\mu$  denotes the average of the sample, xi<br>represents the input properties, N indicates the<br>total number of samples,  $\sigma$  is the variance, ki<br>stands for the normalized sample value, yi is the<br>output after scaling ki where  $\mu$  denotes the average of the sample, xi<br>represents the input properties, N indicates the<br>total number of samples,  $\sigma$  is the variance, ki<br>stands for the normalized sample value, yi is the<br>output after scaling ki represents the imput properties, is minicates the<br>total number of samples, σ is the variance, ki<br>stands for the normalized sample value, yi is the<br>output after scaling ki, ε is a small constant, and<br>γ and β are the scali bustar humber of samples, o is the variance, ki<br>stands for the normalized sample value, yi is the<br>output after scaling ki, e is a small constant, and<br>γ and β are the scaling parameters.<br> $Z'_i = f(x'_i) = \max\{0, x'_i\}$  (8)<br>Where stands for the normalized sample value, yi is the<br>output after scaling ki,  $\varepsilon$  is a small constant, and<br> $\gamma$  and  $\beta$  are the scaling parameters.<br> $Z'_t = f(x'_t) = \max\{0, x'_t\}$  (8)<br>Where  $x'_t$  indicates input and  $Z'_t$  indicat output after scaling ki, ε is a sinant constant, and γ and β are the scaling parameters.<br>  $Z'_t = f(x'_t) = \max\{0, x'_t\}$  (8)<br>
Where  $x'_t$  indicates input and  $Z'_t$  indicates output.<br>
The pooling layer is typically positioned<br>
b *T* and p are the scanng parameters.<br>  $Z'_t = f(x'_t) = \max\{0, x'_t\}$  (8)<br>
Where  $x'_t$  indicates input and  $Z'_t$  indicates output.<br>
The pooling layer is typically positioned<br>
between two consecutive convolution layers and<br>
functi  $Z_t^i = f(x_t^i) = \max\{0, x_t^i\}$  (8)<br>Where  $x_t^i$  indicates input and  $Z_t^i$  indicates output.<br>The pooling layer is typically positioned<br>between two consecutive convolution layers and<br>functions by reducing the size of each feat Where  $x'_i$  indicates input and  $Z'_i$  indicates output.<br>The pooling layer is typically positioned<br>between two consecutive convolution layers and<br>functions by reducing the size of each feature<br>map while maintaining a const The pooling layer is typically positive<br>between two consecutive convolution layers<br>functions by reducing the size of each feature<br>map while maintaining a constant numbe<br>feature maps [19]. Pooling operations<br>include maximum The pooling layer is typically positioned<br>between two consecutive convolution layers and<br>functions by reducing the size of each feature<br>map while maintaining a constant number of<br>feature maps [19]. Pooling operations can<br>i between two consecutive convolution layers and<br>functions by reducing the size of each feature<br>map while maintaining a constant number of<br>feature maps [19]. Pooling operations can<br>include maximum pooling, average pooling, a functions by reducing the size of each feature<br>map while maintaining a constant number of<br>feature maps [19]. Pooling operations can<br>include maximum pooling, average pooling, and<br>sum pooling. Maximum pooling identifies the

multi-class scenarios like faulty bearings. The 3.2.3 Spatial Attention Modul<br>
Tanh function also suffers from gradient Feature Representation<br>
vanishing, risking the loss of important fault CBAM integrates spatial and c<br> map while maintaining a constant number of<br>feature maps [19]. Pooling operations can<br>include maximum pooling, average pooling, and<br>sum pooling. Maximum pooling identifies the<br>highest value within the specified region as t feature maps [19]. Pooling operations can<br>include maximum pooling, average pooling, and<br>sum pooling. Maximum pooling identifies the<br>highest value within the specified region as the<br>output, average pooling computes the mea include maximum pooling, average pooling, and<br>sum pooling. Maximum pooling identifies the<br>highest value within the specified region as the<br>output, average pooling computes the mean of<br>the values, and sum pooling totals th sum pooling. Maximum pooling identifies the highest value within the specified region as the output, average pooling computes the mean of the values, and sum pooling totals the values within the region.<br>3.2.3 Spatial Atten highest value within the specified region as the output, average pooling computes the mean of the values, and sum pooling totals the values within the region.<br>
Fracture Representation Module for Enhanced Scatter Represent output, average pooling computes the mean of<br>the values, and sum pooling totals the values<br>within the region.<br>3.2.3 Spatial Attention Module for Enhanced<br>Feature Representation<br>CBAM integrates spatial and channel attentio the values, and sum pooling totals the values<br>within the region.<br>3.2.3 Spatial Attention Module for Enhanced<br>Feature Representation<br>CBAM integrates spatial and channel attention<br>mechanisms, as illustrated in Figure 8. The within the region.<br>
3.2.3 Spatial Attention Module for Enhanced<br>
Feature Representation<br>
CBAM integrates spatial and channel attention<br>
mechanisms, as illustrated in Figure 8. The<br>
metwork operates on two independent<br>
dim 3.2.3 Spatial Attention Module for Enhanced<br>Feature Representation<br>CBAM integrates spatial and channel attention<br>mechanisms, as illustrated in Figure 8. The<br>network operates on two independent<br>dimensions—channel and spati



*Industry Science and Engineering Vol. 1 No. 7, 2024*<br>
multi-layer perceptron (MLP) with shared this weight is multiplied weights. The MLP applies a sigmoid activation to produce new features<br>
function to process and aggr *Industry Science and Engineering Vol. 1 No. 7, 2024*<br>
multi-layer perceptron (MLP) with shared this weight is multiplied<br>
weights. The MLP applies a sigmoid activation to produce new feature<br>
function to process and aggr

**the Contract of the Control of the Control of the Control of the input features**<br>to produce new features influenced by the channel attention mechanism [20]. this weight is multiplied with the input features<br>to produce new features influenced by the<br>channel attention mechanism [20]. Constrained attention<br>this weight is multiplied with the input features<br>to produce new features influenced by the<br>channel attention mechanism [20].











Example 11 and the second of the second of the second bearings (B21).<br>
By integrating the strengths of VGG-Net and the Convolutional Block Attention Module (CBAM<br>
this model minimizes the loss of fault-bearin<br>
information Figure 8. CBAM Attention Mechanism<br>
By integrating the strengths of VGG-Net and the maps of size 7×7. The third<br>
Convolutional Block Attention Module (CBAM), employs a 2×2 max pooling or<br>
this model minimizes the loss of f Examples and the strengths of VGG-Net and the maps of size 7×7. The Convolutional Block Attention Module (CBAM), employs a 2×2 max poolities model minimizes the loss of fault-bearing same stride, halving the information d By integrating the strengths of VGG-Net and the maps of size  $7\times7$ . The third Convolutional Block Attention Module (CBAM), employs a 2×2 max pooling or this model minimizes the loss of fault-bearing same stride, halving **Example 18 CBAM Attention Mechanism**<br>
By integrating the strengths of VGG-Net and the maps of size 7×7. The the Convolutional Block Attention Module (CBAM), employs a 2×2 max pooling this model minimizes the loss of faul

**Example Follow By integrating the strengths of VGG-Net and the maps of size 7×7. The this Convolutional Block Attention Module (CBAM), employs a 2×2 max pooling of this model minimizes the loss of fault-bearing same stri** By integrating the strengths of VGG-Net and the maps of size '/ $\times$ '. The convolutional Block Attention Module (CBAM), employs a 2 $\times$ 2 max poor information during network propagation. It feature map. combines spatial att Convolutional Block Attention Module (CBAM), employs a  $2 \times 2$  max pooling op this model mimizes the loss of fault-bearing same stride, halving the dime information during network propagation. It feature mp.<br>combines spat this model minimizes the loss of fault-bearing same stride, halving the d<br>information during network propagation. It feature map.<br>combines spatial attention with regularity of Incorporating the CBAM atte<br>change, effective Information during network propagation. It feature map.<br>
combines spatial attention with regularity of Incorporating the CBAM<br>
change, effectively focusing on the task of middle enhances f<br>
infrared thermal imaging (IRT) combines spatial attention with regularity of<br>change, effectively focusing on the task of<br>middle enhances feature<br>infrared thermal imaging (IRT) classification for<br>followed by flattening the need-<br>bearings [21].<br>The algor change, effectively focusing on the task of middle enhances infrared thermal imaging (IRT) classification for followed by flattening to later of 512 neuros. The algorithm model is illustrated in Figure 9. are added, culmi Infrared thermal imaging (IRT) classification for<br>
bearings [21].<br>
The algorithm model is illustrated in Figure 9.<br>
The initial size of the thermal image for friction<br>
The initial size of the thermal image for friction<br>
s bearings [21]. total of 512 neurons. Two<br>
The algorithm model is illustrated in Figure 9.<br>
total of 512 neurons. Two<br>
torque bearings is 691×482 pixels, which is<br>
torque bearings is 691×482 pixels, which is<br>
torque bearin

Spatial<br>Module<br>Module<br>Module<br>maps of size 7×7. The third pooling layer<br>employs a 2×2 max pooling operation with the<br>same stride, halving the dimensions of each<br>feature map.<br>Incorporating the CBAM attention module in the<br>m Attention<br>Module<br>
Module<br> **Example 1980**<br> **Exa Example 19**<br> **The Mechanism**<br>
maps of size 7×7. The third pooling layer<br>
employs a 2×2 max pooling operation with the<br>
same stride, halving the dimensions of each<br>
feature map.<br>
Incorporating the CBAM attention module in **are added**, the readentic beaution of the summary and  $2 \times 2$  max pooling operation with the same stride, halving the dimensions of each feature map.<br>Incorporating the CBAM attention module in the middle enhances feature **shows**<br> **shows**<br> **six a** specifical corresponding the dimensions of size 7×7. The third pooling layer employs a 2×2 max pooling operation with the same stride, halving the dimensions of each feature map.<br>
Incorporating t **Example 12**<br> **https:** TX-7. The third pooling layer<br>
employs a 2×2 max pooling operation with the<br>
same stride, halving the dimensions of each<br>
feature map.<br>
Incorporating the CBAM attention module in the<br>
middle enhance **notion Mechanism**<br> **notion Mechanism**<br>
maps of size  $7\times7$ . The third pooling layer<br>
employs a  $2\times2$  max pooling operation with the<br>
same stride, halving the dimensions of each<br>
feature map.<br>
Incorporating the CBAM atte **ntion Mechanism**<br>maps of size  $7\times7$ . The third pooling layer<br>employs a  $2\times2$  max pooling operation with the<br>same stride, halving the dimensions of each<br>feature map.<br>Incorporating the CBAM attention module in the<br>middle maps of size  $7\times7$ . The third pooling layer<br>employs a  $2\times2$  max pooling operation with the<br>same stride, halving the dimensions of each<br>feature map.<br>Incorporating the CBAM attention module in the<br>incorporating the CBAM a employs a  $2 \times 2$  max pooling operation with the<br>same stride, halving the dimensions of each<br>feature map.<br>Incorporating the CBAM attention module in the<br>middle enhances feature representation,<br>followed by flattening the n same stride, halving the dimensions of each<br>feature map.<br>Incorporating the CBAM attention module in the<br>middle enhances feature representation,<br>followed by flattening the neurons to yield a<br>total of 512 neurons. Two fully feature map.<br>
Incorporating the CBAM attention module in the<br>
middle enhances feature representation,<br>
followed by flattening the neurons to yield a<br>
total of 512 neurons. Two fully connected layers<br>
are added, culminating Incorporating the CBAM attention module in the<br>middle enhances feature representation,<br>followed by flattening the neurons to yield a<br>total of 512 neurons. Two fully connected layers<br>are added, culminating in an output laye

middle enhances feature representation,<br>followed by flattening the neurons to yield a<br>total of 512 neurons. Two fully connected layers<br>are added, culminating in an output layer with<br>bis neurons, each corresponding to a sp followed by flattening the neurons to yield a<br>total of 512 neurons. Two fully connected layers<br>are added, culminating in an output layer with<br>six neurons, each corresponding to a specific<br>bearing state. For optimization, t fotal of 512 neurons. Two fully connected layers<br>are added, culminating in an output layer with<br>six neurons, each corresponding to a specific<br>bearing state. For optimization, the root mean<br>square propagation (RMSprop) algo



**Example 19 Academic Education**<br> **Consequence**<br> **Conseque COMBET CONTROVIDE CONTROVIDED SET ACCEDED ACCEDED ACCEDED ACCEDED AND RELATION CONSTRAINING IN ACCUS AND ACCUSE AND ACCUSE AND CONSIDED AND CONSIDED AND MOVED TO A module, which enhances initial training in bearing fault** (a) Solution Controllery Science and Enginee<br>
Eads to a reduction in loss and an improvement 10 (d) illustrates the com<br>
in accuracy to approximately 95.81%. Figure 10 methods, which enhance<br>
(c) shows the addition of the **Contract Education**<br> **Contract Education**<br> **Contract Education**<br>
In accuracy to a<br>
proximately 95.81%. Figure 10 methods, which enhances<br>
(c) shows the addition of the CBAM attention<br>
module, which enhances initial train **Publishing House**<br> **Publishing House**<br> **Publishing House**<br> **Industry Science and Engineering**<br>
leads to a reduction in loss and an improvement<br>
in accuracy to approximately 95.81%. Figure 10 methods, which enhances the<br>

try Science and Engineering Vol. 1 No. 7, 2024<br>10 (d) illustrates the combined approach of both<br>methods, which enhances the verification rate,<br>reduces iterations, and achieves 100% accuracy<br>in bearing fault classification try Science and Engineering Vol. 1 No. 7, 2024<br>10 (d) illustrates the combined approach of both<br>methods, which enhances the verification rate,<br>reduces iterations, and achieves 100% accuracy<br>in bearing fault classification try Science and Engineering Vol. 1 No. 7, 2024<br>10 (d) illustrates the combined approach of both<br>methods, which enhances the verification rate,<br>reduces iterations, and achieves 100% accuracy<br>in bearing fault classification try Science and Engineering Vol. 1 No. 7, 2024<br>10 (d) illustrates the combined approach of both<br>methods, which enhances the verification rate,<br>reduces iterations, and achieves 100% accuracy<br>in bearing fault classification try Science and Engineering Vol. 1 No. 7, 2024<br>10 (d) illustrates the combined approach of both<br>methods, which enhances the verification rate,<br>reduces iterations, and achieves 100% accuracy<br>in bearing fault classification



**Parameters are calculated:** The extention of Bearing Fault Diagnosis Results 3.3 Diagnosis of Friction Torque Faults Using parameters quantitative characteristics of the there are calculated: the mean (AVG), and constrai STRINGTON CONSULTER THE CONSULTER CONSULTER (C) CONSULTED THE CONSULTED (C) CONSULTED THE CONSULTED THE PCA and SVM<br>
STATE preprocessing the thermal images of training and classification<br>
of training and classification to (CRAM-CNN)<br>
(c) CBAM-CNN<br>
(c) CBAM-CNN<br>
(d) Algorithm in this<br> **Eigure 10. Comparison of Bearing Fault Diagnosis Results**<br>
parameters quantitatively<br> **PCA and SVM**<br>
After preprocessing the thermal images of training and cl Uniformity (UF), and correlation (CL). These<br>
uniformity (U) Algorithm in the Figure 10. Comparison of Bearing Fault Diagnosis Results<br>
Diagnosis of Friction Torque Faults Using<br>
PCA and SVM<br>
After preprocessing the therma

The same of the classification and magnetic services and magnetic services are determined as a crucial foundation of a service is a crucial foundation. Each feature is a crucial foundation. Each feature is a crucial found **Example 12**<br> **Example 12**<br> **normalized by subtraction**<br> **normalized by subtraction**<br> **normalized by subtraction** of the minimum value of<br>
the original thermal image and serve<br>
the original thermal image and dividing by t **Example 12**<br> **Alternal in the original thermal images and served and dividing Fault Diagnosis Results**<br> **Example 12**<br> **Exa Example 12**<br> **Example 12** Figure 1.1 The contract of the contract of the state of a range of [0, 1].<br>
The contract of the thermal images and serve as a crucial foundation for subsequent model<br>
training and classification. Each feature is<br>
normalize **Principal Component Analysis (PCA)** is<br> **Principal Component Analysis (Partna Analysis Results**<br> **Principal Component Analysis (PCA)**<br> **Principal Component Analysis (PCA)**<br> **Principal Component Analysis (PCA)** is<br> **Princ** external to Algorithm in this article<br>
ing Fault Diagnosis Results<br>
parameters quantitatively describe the<br>
characteristics of the thermal images and serve<br>
as a crucial foundation for subsequent model<br>
training and classi (d) Algorithm in this article<br>
ing Fault Diagnosis Results<br>
parameters quantitatively describe the<br>
characteristics of the thermal images and serve<br>
as a crucial foundation for subsequent model<br>
training and classificatio

*Industry Science and Engineering Vol. 1 No. 7, 2024*<br>matrix of the normalized features, maximizing<br>the variance of the transformed data. The<br>features are then sorted based on their<br>corresponding eigenvalues. By selecting **Industry Science and Engineering Vol. 1 No. 7, 2024**<br>
matrix of the normalized features, maximizing<br>
the variance of the transformed data. The<br>
features are then sorted based on their<br>
corresponding eigenvalues. By selec **Industry Science and Engineering Vol. 1 No. 7, 2024**<br>
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the variance of the transformed data. The<br>
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features are then sorted based on their<br>
corresponding eigenvalues. By selec **Industry Science and Engineering Vol. 1 No. 7, 2024**<br>
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the variance of the transformed data. The<br>
features are then sorted based on their<br>
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the variance of the transformed data. The<br>
features are then sorted based on their<br>
corresponding eigenvalues. By selec **Industry Science and Engineering Vol. 1 No. 7, 2024**<br>
matrix of the normalized features, maximizing<br>
the variance of the transformed data. The<br>
features are then sorted based on their<br>
corresponding eigenvalues. By selec **Industry Science and Engineering Vol. 1 No. 7, 2024**<br>
matrix of the normalized features, maximizing<br>
the variance of the transformed data. The<br>
features are then sorted based on their<br>
corresponding eigenvalues. By selec performance. Industry Science and Engineering Vol. 1 No. 7, 2024<br>
matrix of the normalized features, maximizing<br>
the variance of the transformed data. The<br>
features are then sorted based on their<br>
corresponding eigenvalues. By selecti Fraction and Extending linear, maximizing the transformalized features, maximizing the variance of the transformed data. The features are then sorted based on their corresponding eigenvalues. By selecting a specific numbe matrix of the normalized teatures, maximizing<br>the variance of the transformed data. The<br>features are then sorted based on their<br>corresponding eigenvalues. By selecting a<br>specific number of principal components, we<br>control the variance of the transformed data. The<br>
features are then sorted based on their<br>
secreting eigenvalues. By selecting a<br>
specific number of principal components, we<br>
control the variance retained from the original<br>
feat features are then sorted based on their<br>corresponding eigenvalues. By selecting a<br>specific number of principal components, we<br>control the variance retained from the original<br>features, thereby determining the dimensionalit corresponding eigenvalues. By selecting a<br>specific number of principal components, we<br>control the variance retained from the original<br>features, thereby determining the dimensionality<br>reduction helps to eliminate redundant

reduction helps to eliminate redundant features,<br>preventing overfitting and enhancing model<br>In this study, various SVM kernel functions—<br>including linear, polynomial, Gaussian, and<br>including linear, polynomial, Gaussian, a In this study, various SVM kernel tunctions—<br>
including linear, polynomial, Gaussian, and<br>
mechanism and the VGG-N<br>
signoid—are evaluated for classification<br>
success rates. Among these, the quadratic kernel<br>
function prov including linear, polynomial, Gaussian, and<br>
sigmoid—are evaluated for classification on fault detection perfs<br>
success rates. Among these, the quadratic kernel<br>
function proves most effective for handling<br>
complex multi-c sigmoid—are evaluated for classification on fault detection perform<br>success rates. Among these, the quadratic kernel<br>function tests. The result<br>function proves most effective for handling<br>complex multi-class data.<br>To clas success rates. Among these, the quadratic kernel<br>
complex multi-class data.<br>
Complex multi-class data.<br>
To classify unknown samples, we calculate the<br>
complex multi-class data.<br>
To classify unknown samples, we calculate t function proves most effective for handling<br>
function provements are eff<br>
complex multi-class data.<br>
To classify unknown samples, we calculate the<br>
distance between features extracted from<br>
different fault cases and the l complex multi-class data.<br>To classify unknown samples, we calculate the<br>distance between features extracted from<br>different fault cases and the lossless features.<br>Once the distance from the known group<br>exceeds a certain th different fault cases and the lossless features.<br>
The CBAM mix<br>
different fault cases and the lossless features.<br>
the CBAM mix<br>
exceeds a certain threshold, these unknown group<br>
samples can be categorized accordingly. The different fault cases and the lossless teatures.<br>
The CBAM mixed domain atter<br>
exceeds a certain threshold, these unknown<br>
grows Precision and score<br>
exceeds a certain threshold, these unknown<br>
morst significant features i Once the distance from the known group<br>
exceeds a certain threshold, these unknown<br>
smeptes can be categorized accordingly. The six<br>
most significant features identified are M, KU, E,<br>
STD, EN, and KU. During this process exceeds a certain threshold, these unknown<br>
samples can be categorized accordingly. The six<br>
method's ability to effective<br>
moret significant features identified are M, KU, E,<br>
STD, EN, and KU. During this process, PCA<br>
fi samples can be categorized accordingly. The six<br>
most significant features identified are M, KU, E,<br>
smethod's ability to<br>
STD, EN, and KU. During this process, PCA<br>
filters out less relevant features and combines<br>
data u

most significant teatures identified are M, KU, E,<br>
filters out less relevant features and combines<br>
filters out less relevant features and combines<br>
data under the same load into a 6×6 feature<br>
matrix, which serves as th STD, EN, and KU. During this process, PCA information, emphasizin<br>filters out less relevant features and combines the channel and reducing<br>data under the same load into a 6×6 feature sequence number 3, the<br>further classif the sout less relevant teatures and combines<br>
matrix, which serves as the input vector for<br>
further classification, facilitating SVM-based<br>
further classification, facilitating SVM-based<br>
bearing fault diagnosis.<br> **4. Expe** data under the same load into a 6×6 teature<br>
matrix, which serves as the input vector for<br>
further classification, facilitating SVM-based<br>
bearing that VGG-Net effect<br>
bearing fault diagnosis.<br> **4. Experimental Results an** matrix, which serves as the input vector for<br>further classification, facilitating SVM-based<br>bearing fault diagnosis.<br>
Leavening fault diagnosis.<br>  $\begin{array}{ll}\n\text{4. Experimental Results and Discussion} \\
\text{The performance of the proposed algorithm is} \\
\text{reliming that VGG-Net}\n\end{array}$ <br>  $\begin{array}{ll}\n\text{4. Experimental Results and Discussion} \\$ further classification, facilitating SVM-based<br>
bearing fault diagnosis.<br>
4. **Experimental Results and Discussion**<br>
The performance of the proposed algorithm is<br>
comfusion The performance of the proposed algorithm is<br>
com bearing fault diagnosis.<br>
4. Experimental Results and Discussion<br>
The performance of the proposed algorithm is<br>
compared to that of SVM. For multi-class<br>
predictions, the results are organized into a 2D<br>
confusion matrix, **4. Experimental Results and Discussion**<br>
The performance of the proposed algorithm is<br>
compared to that of SVM. For multi-class<br>
predictions, the results are organized into a 2D<br>
sequence number 4 combine<br>
predictions, t **4. Experimental Results and Discussion**<br>
The performance of the proposed algorithm is fusion at each layer.<br>
compared to that of SVM. For multi-class<br>
predictions, the results are organized into a 2D<br>
confusion matrix, w The performance of the proposed algorn<br>compared to that of SVM. For mul<br>predictions, the results are organized into<br>confusion matrix, where each class corre<br>to a "row-by-column" structure. The dime<br>of the matrix reflect t tures identified are M, KU, E,<br>
I. During this process, PCA<br>
I. During this process, PCA<br>
I. During this process and combines<br>
want features and combines<br>
the channel and reducing cla<br>
me load into a 6×6 feature sequence During throusay, First<br>
rand features and combines<br>
the channel and reducing class<br>
enters are the proposed with the sequence number 3, the im<br>
and feature sais the input vector for<br>
adaptive spatial feature fusis<br>
is.<br>
s

$$
Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \times 100\% \quad (9) \qquad \frac{3}{4} \qquad \frac{\times}{4} \qquad \frac{\sqrt{95.75}}{\sqrt{99.84}} \qquad 99.98
$$
\n
$$
Precision = \frac{TP}{TP + FP} \times 100\%; \qquad \qquad 4.2 \qquad Comparison of Fault Diagnosis Outcomes:\n
$$
Precision_{\text{macro}} = \frac{\sum_{i=1}^{L} \text{precision}}{|L|} \qquad \qquad \text{The bearing classification method presented in this article utilizes features extracted from the}
$$
$$

![](_page_7_Picture_8.jpeg)

Re *call* = 
$$
\frac{TP}{TP \times FN} \times 100\%
$$
;  
\nRe *call* = 
$$
\frac{TP}{TP \times FN} \times 100\%
$$
;  
\nRe *call* = 
$$
\frac{\sum_{i=1}^{L} \text{Re call}}{|L|}
$$
;  
\n
$$
\frac{2 \times \text{Precision}_{\text{macro}} \times \text{Recall}_{\text{macro}}}{\text{Precision}_{\text{macro}} + \text{Recall}_{\text{macro}}}
$$
 (12)  
\n**n Experiment**  
\nthe impact of enhanced strategies,  
\n
$$
\frac{PRAM \text{ mixed domain attention}}{\text{transition}}
$$

$$
Recall_{macro} = \frac{\sum_{i=1}^{L} Recall}{|L|}
$$
  
2×Precision × Recall

$$
Flscore_{macro} = \frac{2 \times 11 \text{ Ctsion}_{macro} \times 18 \text{ Ctsion}_{macro}}{\text{Precision}_{macro} + \text{Recall}_{macro}} \quad (12)
$$

specific number of principal components, we<br>
control the variance retained from the original<br>
for the new feature space. This dimensionality<br>
of the new feature space. This dimensionality<br>
reduction helps to eliminate red control the variance retained from the original<br>
features, thereby determining the dimensionality<br>
of the new feature space. This dimensionality<br>
reduction helps to eliminate redundant features,<br>
preventing overfitting an teatures, thereby determining the dimensionality<br>
of the new feature space. This dimensionality<br>
of the new feature space. This dimensionality<br>
precionting overfitting and enhancing model<br>
precionting overfitting and enha of the new teature space. This dimensionality<br>
precenting coeffitting and enhancing model<br>
precenting overfitting and enhancing model<br>
precenting overfitting and enhancing model<br>
preformance.<br>
In this study, various SVM k preventing overfitting and enhancing model<br>
In this study, various SVM kernel functions—<br>
including linear, polynomial, Gaussian, and<br>
including linear, polynomial, Gaussian, and<br>
sigmoid—are evaluated for classification a performance. To evaluate the impact of enhinomics in this study, various SVM kernel functions—<br>including linear, polynomial, Gaussian, and mechanism and the VGG-Net<br>sigmoid—are evaluated for classification on fault detecti signincent returns to entropy the method solidity to effectively utilize features in<br>section of the method soliding the state and continuous terms of soliding the state and continuous terms of soliding the channel and con **Example 10.** The primarion, emphasizing reaveaut leadings and into a 6×6 feature and combines the channel and reducing classification errors as the input vector for sequence number 3, the incorporation of series series a **Property:** Academic Education<br>
Re call =  $\frac{TP}{TP \times FN} \times 100\%$ ;<br>
Re call  $\frac{TP}{TP \times FN} \times 100\%$ ;<br>
Re call  $\frac{2 \times \text{Precision}_{macro}}{|L|}$ <br>
Liscore<sub>mazo</sub> =  $\frac{2 \times \text{Precision}_{macro} \times \text{Recall}_{macro}}{\text{Precision}_{macro} + \text{Recall}_{macro}}$  (12)<br>
Nolation Experiment<br>
valuate the **Contract Education**<br>  $all = \frac{TP}{TP \times FN} \times 100\%;$ <br>  $all_{macro} = \frac{\sum_{i=1}^{L} \text{Re call}}{|L|}$ <br>  $\times \text{Precision}_{macro} \times \text{Recall}_{mono}$  (12)<br> **Precision<sub>necro</sub>** + Recall<sub>necro</sub> (12)<br> **Precision**<sub>necro</sub> + Recall<sub>necro</sub> (12)<br> **Precision**<sub>necro</sub> + Recall<sub>necro</sub> **Propagate 11**<br>  $\text{Recall} = \frac{TP}{TP \times FN} \times 100\%;$ <br>  $\text{Recall}_{\text{macro}} = \frac{\sum_{i=1}^{L} \text{Recall}}{|L|}$ <br>  $\text{Flscore}_{\text{macro}} = \frac{2 \times \text{Precision}_{\text{macro}} \times \text{Recall}_{\text{micro}}}{\text{Precision}_{\text{macro}} + \text{Recall}_{\text{macro}}}$  (12)<br> **Ablation Experiment**<br>
evaluate the impact of enhanced strategi **4.1 Ablation Experiment**<br>
TP  $\frac{TP}{TP \times FN} \times 100\%$ ;<br>  $\text{Re call}_{\text{macro}} = \frac{\sum_{i=1}^{L} \text{Re call}}{|L|}$ <br>  $\text{Flscore}_{\text{macro}} = \frac{2 \times \text{Precision}_{\text{macro}} \times \text{Recall}_{\text{macro}}}{\text{Precision}_{\text{macro}}}$  (12)<br> **4.1 Ablation Experiment**<br>
To evaluate the impact of enhanced strate **1**<br>
Recall =  $\frac{TP}{TP \times FN}$  × 100%;<br>
Recall =  $\frac{TP}{TP \times FN}$  × 100%;<br>
Recall  $\frac{\sum_{i=1}^{L} \text{Re call}}{|L|}$  (11)<br>  $\text{Re call}_{\text{macro}} = \frac{2 \times \text{Precision}_{\text{macro}} \times \text{Recall}_{\text{macro}}}{\text{Precision}_{\text{macro}} + \text{Recall}_{\text{macro}}}$  (12)<br> **4.1 Ablation Experiment**<br>
To evaluate the Re call =  $\frac{TP}{TP \times FN} \times 100\%$ ;<br>
Re call =  $\frac{TP}{TP \times FN} \times 100\%$ ;<br>
Re call  $\frac{1}{|L|}$ <br>
Flscore<sub>ment</sub> =  $\frac{2 \times \text{Precision}_{\text{macro}} \times \text{Recall}_{\text{macro}}}{\text{Precision}_{\text{macro}} + \text{Recall}_{\text{macro}}}$  (12)<br>
4.1 Ablation Experiment<br>
To evaluate the impact of enhanc Re call =  $\frac{TP}{TP \times FN} \times 100\%$ ;<br>
Re call <sub>macro</sub> =  $\frac{\sum_{i=1}^{L} \text{Re call}}{|L|}$ <br>
Flscore<sub>macro</sub> =  $\frac{2 \times \text{Precision}_{\text{macro}} \times \text{Recall}_{\text{macro}}}{\text{Precision}_{\text{macro}} + \text{Recall}_{\text{macro}}}$  (12)<br>
4.1 **Ablation Experiment**<br>
To evaluate the impact of enhanced stra Re call =  $\frac{IP}{TP \times FN} \times 100\%$ ;<br>
Re call <sub>macro</sub> =  $\frac{\sum_{i=1}^{L} \text{Re call}}{|L|}$ <br>
Flscore<sub>macro</sub> =  $\frac{2 \times \text{Precision}_{m\alpha r} \times \text{Recall}_{m\alpha r}}{\text{Precision}_{m\alpha r} + \text{Recall}_{m\alpha r}}$  (12)<br>
4.1 **Ablation Experiment**<br>
To evaluate the impact of enhanced strat TP × FN (11)<br>
Re call<sub>macro</sub> =  $\frac{\sum_{i=1}^{L}$  Re call<br>  $|L|$ <br>
Flscore<sub>macro</sub> =  $\frac{2 \times \text{Precision}_{\text{macro}} \times \text{Recall}_{\text{macro}}}{\text{Precision}_{\text{macro}} + \text{Recall}_{\text{macro}}}$  (12)<br>
4.1 Ablation Experiment<br>
To evaluate the impact of enhanced strategies,<br>
such as Re call<sub>macro</sub> =  $\frac{\sum_{i=1}^{L}$  Re call<br>  $|L|$ <br>  $F$ lscore<sub>mcov</sub> =  $\frac{2 \times \text{Precision}_{\text{macro}} \times \text{Recall}_{\text{macro}}}{\text{Precision}_{\text{macro}} + \text{Recall}_{\text{macro}}}$  (12)<br> **4.1 Ablation Experiment**<br>
To evaluate the impact of enhanced strategies,<br>
such as the CBAM mi Re call<sub>macro</sub> =  $\frac{Z_{i=1}}{|L|}$ <br>
Flscore<sub>macro</sub> =  $\frac{2 \times \text{Precision}_{mzero} \times \text{Recall}_{mzero}}{\text{Precision}_{mzero} + \text{Recall}_{mono}}$  (12)<br>
4.1 **Ablation Experiment**<br>
To evaluate the impact of enhanced strategies,<br>
such as the CBAM mixed domain attention<br>
me Flscore<sub>mare</sub>  $= \frac{2 \times \text{Precision}_{\text{macro}} \times \text{Recall}_{\text{macro}}}{\text{Precision}_{\text{macro}} + \text{Recall}_{\text{mono}}}$  (12)<br> **4.1 Ablation Experiment**<br>
To evaluate the impact of enhanced strategies,<br>
such as the CBAM mixed domain attention<br>
mechanism and the VGG-Net net *Flscore<sub>macro</sub>* =  $\frac{2 \times \text{Precision}_{m\text{zero}} \times \text{Recall}_{m\text{zero}}}{\text{Precision}_{m\text{zero}}}$  (12) <br>**4.1 Ablation Experiment** To evaluate the impact of enhanced strategies, such as the CBAM mixed domain attention mechanism and the VGG-Net network mod FISCOPE<sub>*mace* =  $\frac{m_{\text{max}}}{\text{Precision}_{\text{max}p}}$  + Recall<sub>mace</sub> (12)<br>
4.1 Ablation Experiment<br>
To evaluate the impact of enhanced strategies,<br>
such as the CBAM mixed domain attention<br>
mechanism and the VGG-Net network model,<br>
o</sub> **4.1 Ablation Experiment**<br>To evaluate the impact of enhanced strategies, such as the CBAM mixed domain attention mechanism and the VGG-Net network model, on fault detection performance, we conducted ablation tests. The re **4.1 Ablation Experiment**<br>To evaluate the impact of enhanced strategies,<br>such as the CBAM mixed domain attention<br>mechanism and the VGG-Net network model,<br>on fault detection performance, we conducted<br>ablation tests. The res **4.1 Ablation Experiment**<br>To evaluate the impact of enhanced strategies,<br>such as the CBAM mixed domain attention<br>mechanism and the VGG-Net network model,<br>on fault detection performance, we conducted<br>ablation tests. The re To evaluate the impact of enhanced strategies,<br>such as the CBAM mixed domain attention<br>mechanism and the VGG-Net network model,<br>on fault detection performance, we conducted<br>ablation tests. The results indicate that these<br>i such as the CBAM mixed domain attention<br>mechanism and the VGG-Net network model,<br>on fault detection performance, we conducted<br>ablation tests. The results indicate that these<br>improvements are effective, with Precision and<br>s mechanism and the VGG-Net network model,<br>on fault detection performance, we conducted<br>ablation tests. The results indicate that these<br>improvements are effective, with Precision and<br>experienced as the evaluation metrics. Th on fault detection performance, we conducted<br>ablation tests. The results indicate that these<br>improvements are effective, with Precision and<br>score selected as the evaluation metrics. The<br>experimental results are summarized ablation tests. The results indicate that these<br>improvements are effective, with Precision and<br>score selected as the evaluation metrics. The<br>experimental results are summarized in Table 2.<br>From the findings, it is evident mprovements are effective, with Precision and<br>score selected as the evaluation metrics. The<br>experimental results are summarized in Table 2.<br>From the findings, it is evident that introducing<br>the CBAM mixed domain attention score selected as the evaluation metrics. The<br>experimental results are summarized in Table 2.<br>From the findings, it is evident that introducing<br>the CBAM mixed domain attention mechanism<br>into the backbon network (sequence n experimental results are summarized in Table 2.<br>From the findings, it is evident that introducing<br>the CBAM mixed domain attention mechanism<br>into the backbone network (sequence number 2)<br>improves Precision and score by 3.22 From the findings, it is evident that introducing<br>the CBAM mixed domain attention mechanism<br>into the backbone network (sequence number 2)<br>improves Precision and score by 3.22% and<br>2.09%, respectively. This demonstrates th the CBAM mixed domain attention mechanism<br>into the backbone network (sequence number 2)<br>improves Precision and score by 3.22% and<br>2.09%, respectively. This demonstrates the<br>method's ability to effectively utilize feature<br>i into the backbone network (sequence number 2)<br>improves Precision and score by 3.22% and<br>2.09%, respectively. This demonstrates the<br>method's ability to effectively utilize feature<br>information, emphasizing relevant features mproves Precision and score by 3.22% and 2.09%, respectively. This demonstrates the method's ability to effectively utilize feature information, emphasizing relevant features in the channel and reducing classification err 2.09%, respectively. This demonstrates the<br>method's ability to effectively utilize feature<br>information, emphasizing relevant features in<br>the channel and reducing classification errors. In<br>sequence number 3, the incorporati method's ability to effectively utilize feature<br>information, emphasizing relevant features in<br>the channel and reducing classification errors. In<br>sequence number 3, the incorporation of the<br>adaptive spatial feature fusion n momention, emphasizing relevant features in<br>the channel and reducing classification errors. In<br>sequence number 3, the incorporation of the<br>adaptive spatial feature fusion network VGG-<br>Net results in a 1.8% increase in scor

as the input vector for<br>
adaptive spatial feature fusion network<br>
facilitating SVM-based<br>
Net results in a 1.8% increase in<br>
confirming the VGG-Net effectively are<br>
its and Discussion<br>
the learning of irrelevant features<br> the channel and reducing classification errors. In<br>sequence number 3, the incorporation of the<br>adaptive spatial feature fusion network VGG-<br>Net results in a 1.8% increase in score,<br>confirming that VGG-Net effectively miti sequence number 3, the incorporation of the<br>adaptive spatial feature fusion network VGG-<br>Net results in a 1.8% increase in score,<br>confirming that VGG-Net effectively mitigates<br>the learning of irrelevant features through<br>w adaptive spatial feature fusion network VGG-<br>Net results in a 1.8% increase in score,<br>confirming that VGG-Net effectively mitigates<br>the learning of irrelevant features through<br>wight adjustments, ensuring focused feature<br>f unis in a 1.8% increase in score,<br>the state of the SGG-Net effectively mitigates<br>ring of irrelevant features through<br>adjustments, ensuring focused feature<br>each layer.<br>e number 4 combines both strategies,<br>that this multi-st

![](_page_7_Picture_706.jpeg)

![](_page_7_Picture_707.jpeg)

# 4.2 Comparison of Fault Diagnosis Outcomes:

this article utilizes features extracted from the

![](_page_8_Picture_0.jpeg)

**Categorizing six distinct bearing conditions.** This *Industry Science and Engineering*<br>categorizing six distinct bearing conditions. This across various scenarios. In or<br>study reveals that the proposed method encounter **State of the proposed method**<br> **State of the proposed method**<br> **CALC ACCES**<br> **CAL COMBUT ACCOMORER CONTINUIST ACCORDING THE SURFER CONDUCTS AND THE PROPRET PRODUCTS (SVM) AND THE SURFER CONTINUIST AND THE SURFER Academic Education**<br> **Conserved Fundishing House**<br> **Conserved Fundishing House**<br> **Conserved Fundishing House**<br> **Conserved Engineering**<br>
categorizing six distinct bearing conditions. This across various scenarios. In study **CLE Academic Education**<br> **CLE Academic Education**<br> **CLE Publishing House**<br> **CLE PUBLISHING TOWER THEORY ACTES (SVM)** in across various scenarios. In c<br>
study reveals that the proposed method encounter classification error **CREM Academic Education**<br> **CALCONG PUDISHING HOWER CONCITED ACCES**<br> **CALCONG THEORY SCIPLE MORE THEORY ACCES**<br>
Study reveals that the proposed method encounter classification errors in<br>
outperforms support vector machines **CRE Academic Education**<br> **CREC Publishing House Industry Science and Eng**<br>
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<b>Table 3. Performance COM** (**Table 3. Proposed method** (**SVA**) in healing fault diagnosis. As shown in Table 4, a ssificatio In Imaging the advantages of this and<br>
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![](_page_8_Picture_683.jpeg)

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accuracy Precision Recall F.Score accuracy Precision<br>
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**Example 18 and 19 and 18 and 19 and 19**  $\begin{array}{|l|l|} \hline \text{D} & 0 & 0 & 0 & 881 & 0 \\ \hline \text{D} & 1 & 0 & 0 & 0 & 881 \\ \hline \text{-**SVM and VGG-CBAM-CNN} & & & & \\ \hline \text{VGG-CBAM-CNN} & & & \\ \hline \text{accuracy} & \text{Precision} & \text{Recall} & \text{F.Score} \\ \hline \text{99.83} & 98.23 & 99.51 & 92.97 \\ \hline \text{100} & 99.31 & 99.64 & 91.42 \\ \hline \text{99.83} & 99.21**$ fault scenarios. The proposed CNN method **EXECT ANTION SET USING A CONSTRESS CONSTRESS SECT ANTI-ORIGATION**<br> **EXECUTE 100 PECISION Recall F.Score**<br> **99.83 98.23 99.51 92.97**<br> **100 99.31 99.64 91.42**<br> **100 99.67 99.12 99.48**<br> **100 99.67** VGG-CBAM-CNN<br>
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including thermal images of bearings,<br>
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this approach for diagnosing bearing torque<br>
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## **Acknowledgments**

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- ding thermal images of bearings,<br>eving a classification accuracy of 99.80%.<br>se findings underscore the advantages of<br>approach for diagnosing bearing torque<br>ts.<br>nowledgments<br>spaper was supported by Tianjin<br>mece and Technolo eving a classification accuracy of 99.80%.<br>See findings underscore the advantages of<br>approach for diagnosing bearing torque<br>ts.<br>nowledgments<br>spaper was supported by Tianjin<br>mece and Technology Plan Project under<br>t 23YDTPJC se tindings underscore the advantages of<br>approach for diagnosing bearing torque<br>ts.<br>mowledgments<br>paper was supported by Tianjin<br>mcc and Technology Plan Project under<br>t 23YDTPJC00290.<br>**erences**<br>Choudhary A, Mian T, Fatima S approach for diagnosing bearing torque<br>ts.<br> **nowledgments**<br>
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