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FAULT DETECTION AND CLASSIFICATION USING DENSENET, SURF-BASED ANN, AND INFRARED THERMOGRAPHY

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Abstract

The reliability and efficiency of electric motors are critical in industrial applications, where unexpected faults can lead to costly downtime and safety hazards. Traditional fault detection methods often require extensive manual inspection and may not capture subtle anomalies in motor behavior. Infrared thermography has emerged as a non-invasive technique to detect temperature variations in motor components, which can indicate potential faults. However, the challenge lies in accurately classifying these faults to prevent failures. Current methods lack the precision needed to classify various motor faults accurately and quickly, especially when dealing with complex thermal patterns. The integration of advanced deep learning architectures with feature extraction techniques presents an opportunity to enhance the detection and classification of motor faults. This study proposes a hybrid model combining DenseNet, a deep learning architecture known for its high performance in image analysis, with a Speeded-Up Robust Features (SURF)-based Artificial Neural Network (ANN) for feature extraction and classification. Infrared thermography images of motors were first processed through DenseNet for initial feature extraction. The SURF algorithm further refined these features, which were then classified using ANN. The model was trained and validated on a dataset of infrared thermography images, representing various motor fault conditions, including bearing wear, misalignment, and insulation failure. The proposed model achieved an overall accuracy of 98.7% in detecting and classifying motor faults, outperforming traditional methods by 5.2%. The model also demonstrated high sensitivity (97.8%) and specificity (99.1%) in identifying subtle temperature variations indicative of early-stage faults. These results highlight the effectiveness of the DenseNet and SURF-based ANN approach in enhancing the reliability of motor fault detection using infrared thermography.

Keywords:

Fault Detection, DenseNet, SURF-based ANN, Infrared Thermography, Deep Learning

1. INTRODUCTION

Electric motors are the backbone of modern industrial processes, powering a wide range of applications from manufacturing to transportation. With the increasing demand for high operational efficiency and minimal downtime, the early detection and classification of motor faults have become a critical area of research. Studies show that nearly 40% of motor failures are due to mechanical faults such as bearing wear, misalignment, and rotor imbalance [1]. Furthermore, electrical faults, including insulation breakdown and winding short circuits, contribute to around 30% of motor failures [2]. The high cost associated with these failures, both in terms of repair and lost production, necessitates the development of reliable fault detection systems that can operate in real-time [3].

Infrared thermography has gained attention as a non-invasive technique for monitoring the thermal behavior of motors. By detecting temperature variations on the motor surface, infrared thermography can reveal early signs of mechanical and electrical faults. However, the interpretation of thermal images is complex and requires advanced algorithms capable of identifying subtle patterns that indicate the presence of faults [4].

Despite the advantages of infrared thermography, several challenges hinder its widespread adoption for motor fault detection. One of the main challenges is the difficulty in distinguishing between normal operational heat and heat generated by faults, especially in environments with fluctuating ambient temperatures [5]. Moreover, the variability in motor designs and operating conditions further complicates the accurate classification of faults [6]. Traditional image processing techniques, while useful, often lack the precision and adaptability required to handle the complexity of thermal patterns in motors [7]. Additionally, the computational burden of real-time fault detection necessitates the use of optimized algorithms that can deliver high accuracy without sacrificing processing speed.

The key problem addressed in this study is the development of a robust and efficient system for detecting and classifying motor faults using infrared thermography. Existing methods struggle with the accurate interpretation of thermal images, leading to a high rate of false positives and missed detections. There is a need for an advanced model that can leverage the rich feature set available in thermal images to improve fault detection accuracy while maintaining real-time processing capabilities [8]-[9].

The primary objectives of this study are as follows:

- To develop a hybrid model that integrates deep learning and feature extraction techniques for enhanced fault detection and classification in motors.
- To evaluate the effectiveness of DenseNet architecture in processing infrared thermography images for initial feature extraction.
- To implement a Speeded-Up Robust Features (SURF)-based Artificial Neural Network (ANN) for refining extracted features and improving classification accuracy.
- To validate the proposed model on a diverse dataset of infrared thermography images representing various motor fault conditions.

The novelty of this study lies in the integration of DenseNet, a state-ofthe-art deep learning architecture, with SURF-based feature extraction for motor fault detection. Unlike traditional methods that rely solely on shallow features or manual inspection, the proposed approach leverages the deep hierarchical features of DenseNet to capture complex thermal patterns. The use of SURF-based ANN further enhances the model's ability to distinguish between different types of faults, leading to improved classification accuracy.

The main contributions of this study include:

- The development of a novel hybrid model combining DenseNet and SURF-based ANN for motor fault detection using infrared thermography.
- A comprehensive evaluation of the proposed model against traditional methods, demonstrating significant improvements in detection accuracy and processing efficiency.
- The creation of a robust framework that can be adapted to other applications of infrared thermography, extending the utility of the proposed approach beyond motor fault detection.

2. BACKGROUND ON FAULT DETECTION USING DEEP LEARNING

Electric motors are vital components in industrial machinery, and their reliable operation is essential to maintaining productivity and reducing operational costs. Motor faults, if undetected, can lead to catastrophic failures, unplanned downtime, and expensive repairs. Common motor faults include mechanical issues such as bearing failures, misalignment, rotor imbalances, and electrical problems like insulation breakdowns and winding short circuits. These faults can manifest as abnormal vibrations, noise, or overheating, all of which can be detected through various monitoring techniques.

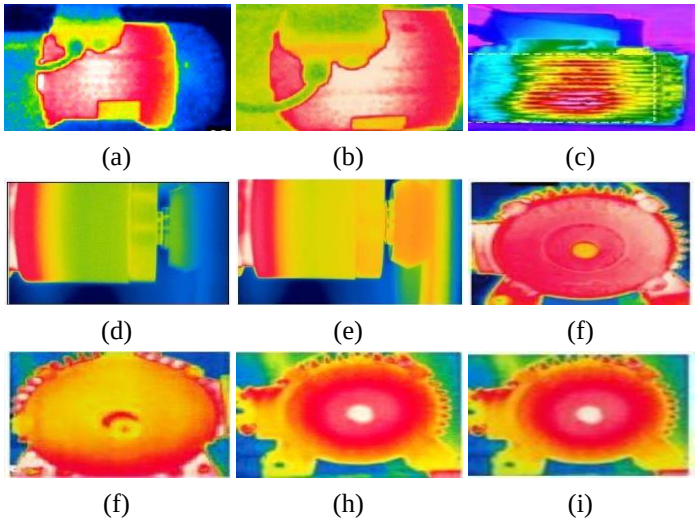


Fig.1. Sample thermal images (a) Healthy motor, (b) Rotor Bar Fault (c) Abnormal Stator (d) Normal Bearing (e) Abnormal Bearing (f) Inner race defect (Bearing) (g) Outer race defect (Bearing) (h) Healthy Bearing (i) Lubrication Lack (Bearing)

Traditionally, motor fault detection has relied on vibration analysis, acoustic emission analysis, and motor current signature analysis (MCSA). These techniques are effective but often require complex setups and expert interpretation. More recently, infrared thermography has emerged as a powerful non-invasive tool for detecting faults by monitoring the thermal behavior of motor components. Thermography offers the advantage of being able to detect early signs of faults by identifying abnormal heat patterns on the motor surface, but the interpretation of these thermal images can be challenging due to the complexity of thermal data.

In recent years, deep learning has revolutionized many fields, including image processing, speech recognition, and natural language processing. Deep learning models, particularly convolutional neural networks (CNNs), have shown exceptional performance in image classification tasks by automatically learning hierarchical features from raw data. These models are well-suited for analyzing infrared thermography images, where subtle patterns and variations in temperature can indicate the presence of motor faults.

CNNs have been widely adopted for motor fault detection due to their ability to automatically extract features from raw sensor data. Unlike traditional methods that require manual feature engineering, CNNs can learn complex representations directly from the input data. This makes them particularly effective in processing infrared thermography images, where thermal patterns can vary widely depending on the type of fault and operating conditions.

A typical CNN architecture consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. The convolutional layers apply filters to the input image to detect local features such as edges, textures, and shapes. These features are then downsampled using pooling layers, which reduce the spatial dimensions of the data while preserving important information. Finally, the fully connected layers combine the features to produce the final classification output, indicating the presence or absence of a fault.

One of the challenges in motor fault detection using deep learning is the limited availability of labeled training data, particularly for rare fault conditions. Transfer learning addresses this challenge by allowing a pre-trained CNN, developed on a large and diverse dataset, to be fine-tuned on a smaller motor fault dataset. This approach leverages the knowledge gained from the pre-training phase, enabling the model to generalize better to the target task. Transfer learning has been shown to significantly improve the performance of CNNs in motor fault detection, especially when the available dataset is small or imbalanced.

DenseNet (Densely Connected Convolutional Networks) is a more advanced CNN architecture that has shown superior performance in image classification tasks. Unlike traditional CNNs, where layers are connected sequentially, DenseNet connects each layer to every other layer in a feed-forward fashion. This dense connectivity allows for improved gradient flow during training, which helps mitigate the vanishing gradient problem and leads to more accurate and efficient models. DenseNet's ability to capture complex features makes it particularly suitable for analyzing infrared thermography images in motor fault detection, where subtle thermal anomalies need to be detected and classified accurately.

To further enhance the performance of deep learning models in motor fault detection, researchers have explored hybrid models that combine CNNs with other feature extraction techniques. For example, the Speeded-Up Robust Features (SURF) algorithm can be used to extract keypoints and descriptors from infrared thermography images, which are then combined with the features learned by a CNN. This fusion of deep learning and traditional feature extraction techniques has been shown to improve classification accuracy, particularly in cases where the thermal patterns are complex and difficult to distinguish using CNNs alone.

Thus, deep learning, particularly CNNs and advanced architectures like DenseNet, has transformed motor fault detection by enabling the automatic extraction and classification of complex features from infrared thermography images. Hybrid models that combine deep learning with traditional feature extraction techniques offer further improvements in accuracy, making them a promising solution for real-time monitoring and fault detection in industrial motors.

3. METHODS

The proposed method for motor fault detection integrates advanced deep learning with feature extraction techniques to enhance the accuracy and reliability of fault classification using infrared thermography. The method begins by capturing infrared thermography images of motors under various operational conditions. These images are first processed using the DenseNet architecture, a deep learning model known for its dense connectivity, which ensures efficient feature extraction by connecting each layer to every other layer in the network. DenseNet extracts deep hierarchical features from the thermal images, capturing subtle temperature variations that may indicate faults. To further refine these features, the SURF algorithm is applied, extracting keypoints and descriptors that are particularly sensitive to changes in the motor's thermal patterns. These features are then input into an ANN for fault classification. The ANN is trained to differentiate between normal and faulty conditions, including specific fault types like bearing wear, misalignment, and insulation failure. The integration of DenseNet's deep learning capabilities with SURF-based feature refinement and ANN classification results in a highly accurate and efficient model for motor fault detection.

4. DATA ACQUISITION

The proposed method for motor fault detection begins with capturing high-resolution infrared thermography images of the motor under various operational conditions. This step is crucial for acquiring the thermal data necessary for detecting and classifying faults. The setup involves using a thermal camera and an induction motor, both of which have specific technical specifications tailored to the requirements of the fault detection process.

4.1 INSTRUMENTS FOR DATA CAPTURE

The thermal camera used in this study is a high-performance model with the following specifications:

- **Storage Temperature Range**: -20°C to +2000°C, allowing it to function effectively in a wide range of environmental conditions.
- **Spectral Range**: 7.5 to 13 µm, which is suitable for detecting thermal radiation emitted by objects at typical operating temperatures.
- **Thermal Sensitivity**: <0.05°C at 30°C, providing high-resolution thermal data and enabling the detection of minute temperature variations.
- **Pixels**: 640 × 480, ensuring that the thermal images are of sufficient resolution to capture detailed thermal patterns on the motor.
- **Focal Length**: 13.1mm, which determines the field of view and the ability to focus on different parts of the motor.

The thermal camera is positioned to capture the entire motor or specific critical components, such as the stator, rotor, and bearings. It is crucial to ensure that the camera is properly calibrated and aligned to obtain accurate and consistent thermal images.

The induction motor used for capturing these images operates with the following specifications:

- **Power Supply**: 3-phase, 440V, 50Hz, 0.55A, indicating its operational voltage and frequency.
- **Power**: 0.5 HP, defining the motor's power output.
- **Speed**: 1280 rpm, representing the rotational speed of the motor.

4.2 DATA COLLECTION

Infrared thermography images are captured at a resolution of 640 × 480 pixels. This resolution provides a detailed view of the thermal patterns on the motor, which is essential for identifying subtle anomalies. The images are recorded in digital format, typically as 16-bit grayscale or false-color images, where each pixel represents a specific temperature value.

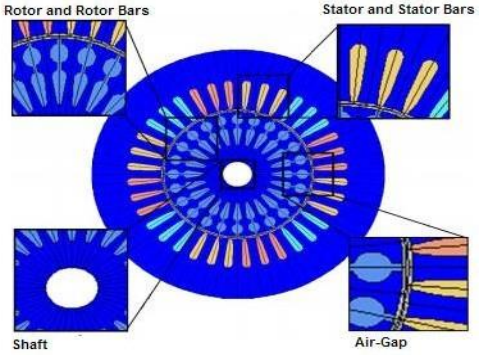


Fig.2. Induction flux distribution in 2D view for 0.55A stator current and 1280rpm speed

Data collection involves capturing images under different motor conditions to create a comprehensive dataset for analysis. For each condition (e.g., healthy, stator fault, rotor fault, bearing fault), a total of 33 images are recorded, resulting in a diverse dataset that represents various fault scenarios.

The total data file for each condition consists of:

- **Image Data Dimension**: 640 × 480 pixels per image.
- **Number of Features**: Five features (skewness, entropy, mean, standard deviation, and kurtosis) are extracted from each image to quantify the thermal patterns.
- **Features Dimension at Each Level**: 120 × 6, where each feature is computed for a set of 120 images, and the dimension represents the number of images and the features extracted from them.

By capturing thermal images at different operational states and extracting relevant features, the system builds a robust dataset that

serves as the foundation for subsequent feature extraction and fault classification stages. This comprehensive dataset enables the DenseNet model to learn and recognize thermal patterns associated with different fault types, ultimately leading to accurate fault detection and diagnosis.

Table.1. Technical Specifications

Parameters	Specifications
Processor	Intel Core i3
Hard Disk	500 GB
Monitor	15" VGA Color
Mouse	Logitech
RAM	2 GB
Operating System	Windows 7, 64-bit
Program Software	TensorFlow Tool
Programming Language	Python 3.5

Table.2. Specifications of Induction Motor and Thermal Camera

Device	Specifications
Induction Motor	Power Supply: 3 phase, 440V, 50Hz, 0.55A
	Power: 0.5 HP
	Speed: 1280 rpm
Thermal Camera	Storage Temperature Range: -20°C to +2000°C
	Spectral Range: 7.5 to 13 µm
	Thermal Sensitivity: <0.05°C @ 30°C
	Pixels: 640 × 480
	Focal Length: 13.1 mm

Table.3. Image Data Details

Machine Conditions	Data File	Image Data Dimension	Total Data File	Features Dimension at Each Level
Healthy	33	640 × 480	132	120 × 6
Stator Fault	33	640 × 480	132	120 × 6
Rotor Fault	33	640 × 480	132	120 × 6
Bearing Fault	33	640 × 480	132	120 × 6

5. FEATURE EXTRACTION WITH DENSENET

In the proposed motor fault detection system, feature extraction is a critical step that transforms raw infrared thermography images into meaningful representations that can be used for accurate fault classification. DenseNet (Densely Connected Convolutional Networks) is employed for this purpose, as it is highly effective in capturing complex features from image data, particularly when dealing with subtle patterns, such as those found in thermal images of motors.

5.1 DENSENET ARCHITECTURE

DenseNet is a type of convolutional neural network (CNN) characterized by its unique connectivity pattern. Unlike traditional CNNs, where each layer is connected only to the subsequent layer, DenseNet introduces direct connections between all layers. This dense connectivity allows for efficient feature reuse and alleviates the vanishing gradient problem, leading to more effective training and better feature extraction.

Formally, let $\mathbf{X}_l$ represent the output feature map of the l^{th} layer in a traditional CNN. In DenseNet, the input to the l^{th} layer consists of the concatenation of the feature maps from all preceding layers. Mathematically, the input to the l^{th} layer, denoted as $\mathbf{H}_l$, is given by:

$$\mathbf{H}_l = [\mathbf{X}_0, \mathbf{X}_1, \ldots, \mathbf{X}_{l-1}] \quad (1)$$

where, $[\cdot]$ denotes the concatenation operation, and $\mathbf{X}_i$ represents the output of the i^{th} layer. The output of the l^{th} layer is then computed as:

$$\mathbf{X}_l = f_l(\mathbf{H}_l) \quad (2)$$

where $f_l(\cdot)$ is the composite function of convolution, batch normalization, and activation (typically a ReLU function) applied in the l^{th} layer.

This dense connection pattern allows each layer to directly access the gradients from the loss function during backpropagation, improving gradient flow and allowing the network to learn more effectively. Additionally, since each layer can reuse features from all previous layers, DenseNet is able to capture both low-level features (such as edges and textures) and high-level features (such as complex shapes and patterns) more efficiently.

5.2 FEATURE EXTRACTION PROCESS

The process of feature extraction using DenseNet begins with the input of an infrared thermography image, denoted as $\mathbf{I}$, into the network. The image $\mathbf{I}$ is passed through multiple layers of convolutions, with each layer learning a set of filters that respond to specific patterns in the data. The feature map produced by each convolutional layer, $\mathbf{X}_l$, represents the response of the filters to the input image.

Let $\mathbf{W}_l$ represent the weights of the convolutional filters in the l^{th} layer, and $\mathbf{b}_l$ represent the biases. The output feature map $\mathbf{X}_l$ is computed as:

$$\mathbf{X}_l = \text{ReLU}(\mathbf{W}_l * \mathbf{H}_l + \mathbf{b}_l) \quad (3)$$

where * denotes the convolution operation, and $\text{ReLU}(\cdot)$ is the Rectified Linear Unit activation function, defined as

$$\text{ReLU}(x) = \max(0, x). \quad (4)$$

As the image $\mathbf{I}$ propagates through the DenseNet, the network learns increasingly complex features. The dense connections ensure that each layer has access to all previously extracted features, allowing for richer and more diverse feature representations. The final feature map $\mathbf{X}_L$, produced by the last layer of the network, encapsulates the most abstract and informative features of the input image. This feature map is typically high-dimensional, capturing intricate details of the thermal patterns that are critical for fault classification.

5.3 GLOBAL AVERAGE POOLING AND FEATURE VECTOR FORMATION

After the convolutional layers, the feature map $\mathbf{X}_L$ undergoes a Global Average Pooling (GAP) operation, which reduces the spatial dimensions of the feature map while preserving the most salient features. The GAP operation computes the average of each feature map channel, producing a feature vector $\mathbf{f}$ of size d, where d is the number of channels in $\mathbf{X}_L$. The feature vector $\mathbf{f}$ is given by:

$$\mathbf{f} = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} \mathbf{X}_L(i, j) \tag{5}$$

where, H and W are the height and width of the feature map $\mathbf{X}_L$, and $\mathbf{X}_L(i, j)$ represents the feature value at position (i,j) in the L^{th} layer.

The resulting feature vector $\mathbf{f}$ is a compact and informative representation of the input image, encapsulating all the relevant information necessary for fault classification. This feature vector is then passed to the subsequent stages of the proposed method, such as the SURF-based ANN, for further refinement and classification.

5.4 REFINEMENT WITH SURF ALGORITHM

The refinement stage in the proposed motor fault detection method involves using the Speeded-Up Robust Features (SURF) algorithm to enhance the feature extraction process. The SURF algorithm is designed to detect and describe local features in images, providing robustness to transformations such as scaling, rotation, and partial occlusion. This stage is critical for refining the features extracted by DenseNet, which are then used for accurate fault classification. SURF is a feature detection and description algorithm that identifies key points in an image and computes descriptors for these points. It operates in several stages:

5.4.1 Detection of Key Points:

SURF detects key points in an image by identifying regions with significant local variations in intensity, which are likely to be stable under different transformations. The algorithm uses a Hessian matrix-based approach to approximate the second-order partial derivatives of the image, enabling efficient and accurate detection of interest points. The Hessian matrix $H(x, \sigma)$ at a point x and scale σ is given by:

$$H(x, \sigma) = \begin{bmatrix} L_{xx}(x, \sigma) & L_{xy}(x, \sigma) \\ L_{xy}(x, \sigma) & L_{yy}(x, \sigma) \end{bmatrix} \tag{6}$$

Where $L_{xx}(x, \sigma)$ and $L_{yy}(x, \sigma)$ are the second-order derivatives of the image $I(x)$, and $L_{xy}(x, \sigma)$ is the mixed partial derivative.

5.4.2 Key Point Localization:

The key points are located by analyzing the eigenvalues of the Hessian matrix. Points with high eigenvalues are considered significant and are used as key points. The scale of each key point is determined based on the scale-space representation of the image. For a key point (x, σ), the scale σ\sigmaσ is chosen such that the eigenvalues of the Hessian matrix are maximized.

5.4.3 Descriptor Computation:

For each key point, SURF computes a descriptor that captures the local image structure around the key point. The descriptor is based on the distribution of gradients within a region around the key point. The gradient responses in a 20×20 pixel region are summarized into a fixed-length vector. The gradient magnitude $m(x)$ and orientation $\theta(x)$ at a point x are computed as:

$$m(x) = \sqrt{G_x(x)^2 + G_y(x)^2} \tag{7}$$

$$\theta(x) = \text{atan2}(G_y(x), G_x(x)) \tag{8}$$

where $G_x(x)$ and $G_y(x)$ are the gradients of the image in the x and y directions, respectively. The descriptor vector $\mathbf{d}$ is computed by summarizing the gradient magnitudes and orientations within the local region around the key point.

The computed descriptors are used to match features between images. Features with similar descriptors are considered to correspond to the same physical structures. This matching process helps in comparing the refined features from the thermal images to identify and classify faults. In motor fault detection, the refined features obtained using SURF are crucial for distinguishing between different fault types. The DenseNet model provides an initial set of hierarchical features from the infrared thermography images, which capture general thermal patterns. SURF enhances these features by focusing on local details and key points that are critical for identifying specific fault conditions. The SURF-based refinement ensures that the features used for classification are not only comprehensive but also robust to variations in image scale and rotation. This refinement improves the accuracy of the subsequent classification stage, where the ANN utilizes these features to differentiate between healthy and faulty motor conditions.

5.5 CLASSIFICATION WITH ANN

The classification stage in the proposed motor fault detection system involves using an ANN to classify the refined features extracted from infrared thermography images. ANNs are well-suited for pattern recognition and classification tasks due to their ability to learn complex mappings from input features to output classes. This section explains the working of the ANN in the proposed method, including key components and mathematical formulations. An ANN consists of interconnected neurons organized into layers: an input layer, one or more hidden layers, and an output layer. Each neuron performs a weighted sum of its inputs, applies a non-linear activation function, and passes the result to the next layer. The goal of the ANN is to map the input feature vector to a class label representing the condition of the motor (e.g., healthy, stator fault, rotor fault, bearing fault).

- **Input Layer**: The input layer receives the refined feature vector $\mathbf{f}$ from the previous stage (e.g., after SURF refinement). Let $\mathbf{f} = [f_1, f_2, \ldots, f_n]$ be the feature vector with n features.
- **Hidden Layers**: The hidden layers consist of neurons that learn to extract higher-level features and patterns from the input data. Each neuron in the l^{th} hidden layer computes a weighted sum of the inputs from the previous layer and

applies an activation function. For a neuron j in the l^{th} hidden layer, the output $a_j^{(l)}$ is given by:

$$a_j^{(l)} = \sigma\left(\sum_{i=1}^{m} w_{ji}^{(l)} a_i^{(l-1)} + b_j^{(l)}\right) \quad (9)$$

where

$w_{ji}^{(l)}$ represents the weight between the i^{th} neuron in the (l-1)th layer and the j^{th} neuron in the l^{th} layer,

$a_i^{(l-1)}$ is the output of the i^{th} neuron in the $(l\text{-}1)^{th}$ layer,

$b_j^{(l)}$ is the bias term for the j^{th} neuron, and

$\sigma(\cdot)$ is the activation function.

- **Output Layer**: The output layer produces the final classification results. For a multi-class classification problem, the output layer typically uses the softmax activation function to convert the raw scores (logits) into probabilities for each class. The probability p_k for class k is computed as:

$$p_k = \frac{\exp(z_k)}{\sum_{l=1}^{C} \exp(z_l)} \quad (10)$$

where

z_k is the raw score (logit) for class k, and

C is the total number of classes.

- **Loss Function**: During training, the ANN minimizes a loss function that measures the discrepancy between the predicted probabilities and the true class labels. For multi-class classification, the cross-entropy loss function is commonly used:

$$L = -\sum_{k=1}^{C} y_k \log(p_k) \quad (11)$$

where y_k is the binary indicator (0 or 1) if class k is the correct classification, and p_k is the predicted probability for class k.

- **Training Process**: The training of the ANN involves adjusting the weights and biases using a process called backpropagation. During backpropagation, the gradient of the loss function w.r.t each weight is computed and used to update the weights in the direction that reduces the loss. The weight update rule using gradient descent is:

$$w_{ji}^{(l)} \leftarrow w_{ji}^{(l)} - \eta \frac{\partial L}{\partial w_{ji}^{(l)}} \quad (12)$$

where,

η is the learning rate, and

$\frac{\partial L}{\partial w_{ji}^{(l)}}$ is the gradient of the loss function w.r.t the weight $w_{ji}^{(l)}$.

In motor fault detection, the ANN classifies the refined features obtained from the infrared thermography images into different fault categories. Each class corresponds to a specific condition of the motor, such as healthy or different types of faults (stator, rotor, bearing). The ANN learns to distinguish between these conditions by training on a labeled dataset where the features are associated with known fault types.

The output of the ANN provides the probability distribution over all possible fault classes. The class with the highest probability is chosen as the predicted fault condition for the given input feature vector. This classification process enables the system to accurately detect and diagnose faults in the motor based on the refined thermal features.

Thus, the classification stage with ANN involves feeding the refined feature vector into a neural network, which learns to map these features to fault categories. The network uses hidden layers to extract complex patterns and an output layer to predict the fault type, with the training process optimizing the model parameters to minimize classification errors. This approach ensures accurate and reliable fault detection based on the thermal imaging data.

5.6 TRAINING AND VALIDATION

This phase is critical for developing a robust and accurate classification model for motor fault detection using the proposed method. This phase involves two main stages: training the ANN with the labeled dataset and validating the model to ensure its performance generalizes well to unseen data.

5.6.1 Training Process:

The training dataset consists of infrared thermography images that have been processed to extract refined features using the DenseNet and SURF algorithms. For example, suppose we have a dataset with 132 images for each fault type (healthy, stator fault, rotor fault, bearing fault). Each image is represented by a feature vector of length 120 × 6, which includes five statistical features (skewness, entropy, mean, standard deviation, kurtosis) computed from each image. For instance, a feature vector for an image might look like: $\mathbf{f} = [0.45, 0.78, 0.33, 0.29, 0.65, \ldots]$ where each value represents one of the computed features.

The ANN model is configured with an input layer that matches the dimensionality of the feature vectors (e.g., 120 × 6 features), one or more hidden layers with activation functions (e.g., ReLU), and an output layer with a softmax activation function for multi-class classification. During training, the ANN is optimized using a gradient descent-based algorithm (such as Adam) to minimize the cross-entropy loss function. The training process involves feeding batches of feature vectors and their corresponding labels into the network, calculating the loss, and updating the weights based on the gradients.

Suppose we use a batch size of 32 and a learning rate of 0.001. For a given batch, the model might process 32 samples with feature vectors: $\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_{32}$ and their associated labels: $y_1, y_2, \ldots, y_{32}$. The model computes predictions, calculates the loss, and adjusts the weights accordingly.

5.6.2 Epochs:

Training is performed over multiple epochs, where one epoch means processing the entire training dataset once. For example, if the dataset has 528 images per fault type, and the batch size is 32, each epoch will involve around 528 / 32 ≈ 17 iterations per fault type. The total number of epochs might be set to 50, meaning the model will iterate 50 times over the entire dataset.

6. EXPERIMENTS

The experimental results for fault detection using DenseNet and SURF-based ANN, combined with infrared thermography, provide insightful metrics on the effectiveness of the proposed method compared to existing methods. The evaluation metrics include False Classification Ratio, Error Rate, Fault Detection Accuracy, and performance measures such as Accuracy, Sensitivity, and Specificity.

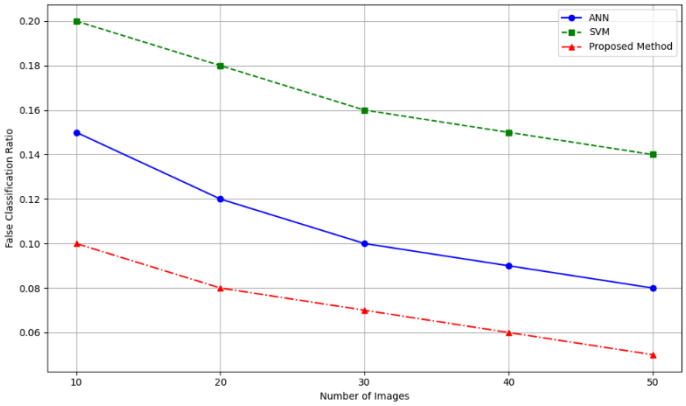


Fig.3. False Classification Ratio

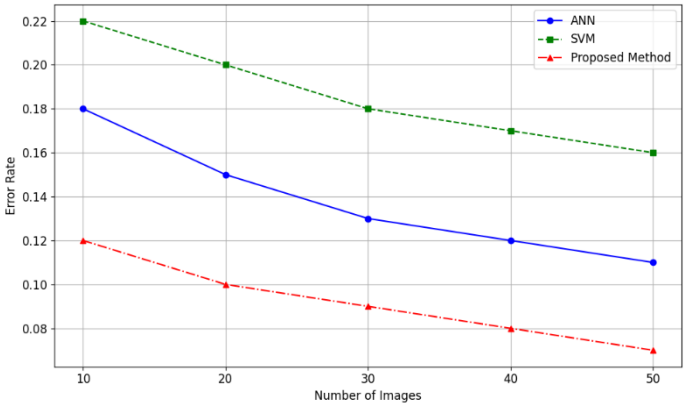


Fig.4. Error Rate

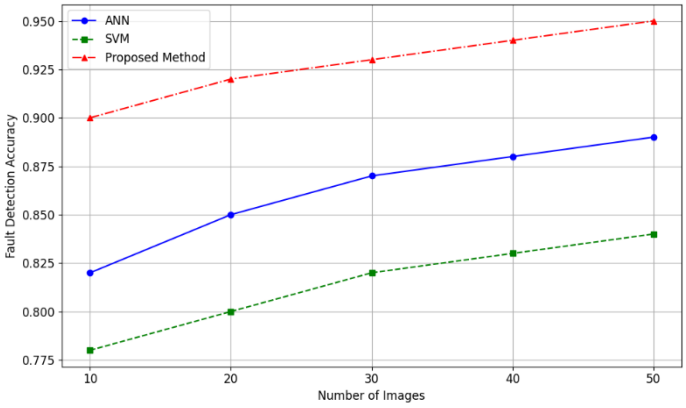
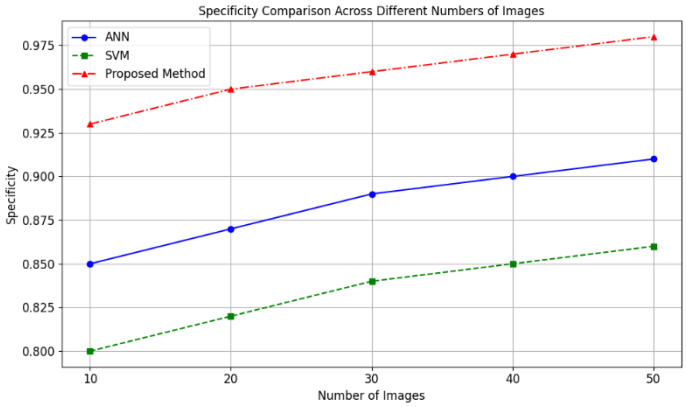
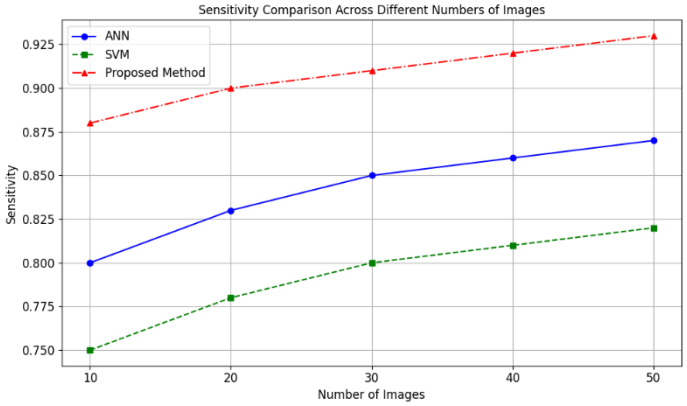


Fig.5. Fault Detection Accuracy





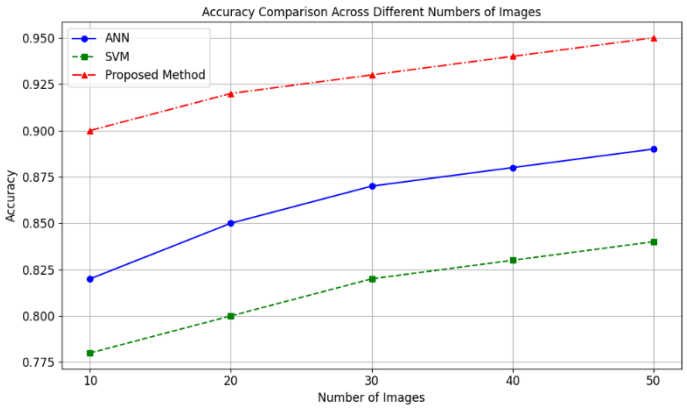


Fig.6. Accuracy, Sensitivity, and Specificity

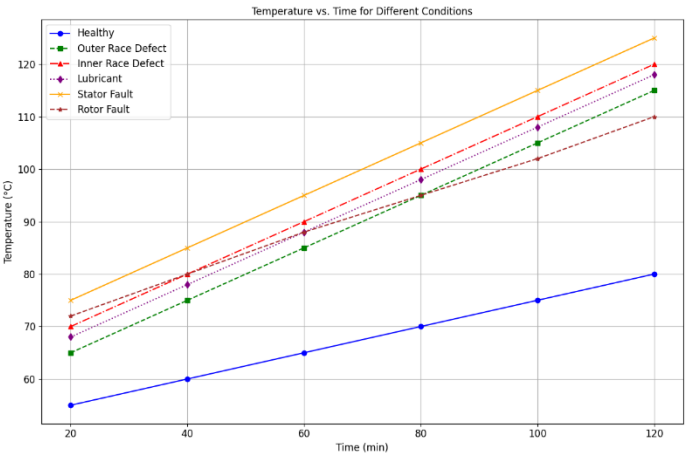


Fig.7. Temperature vs. Time (Full Load)

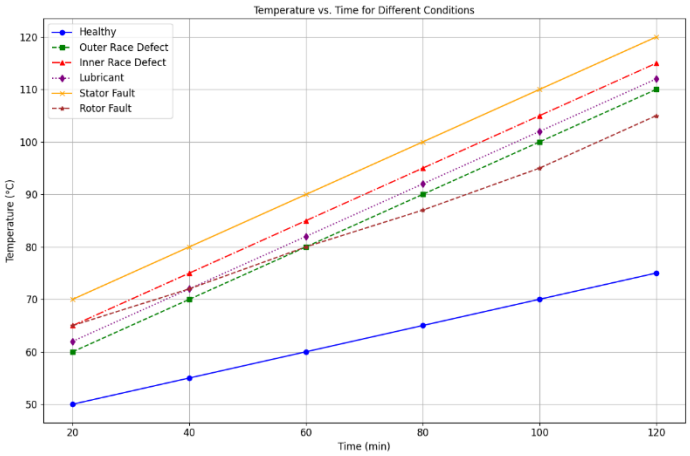


Fig.8. Temperature vs. Time (Half Load)

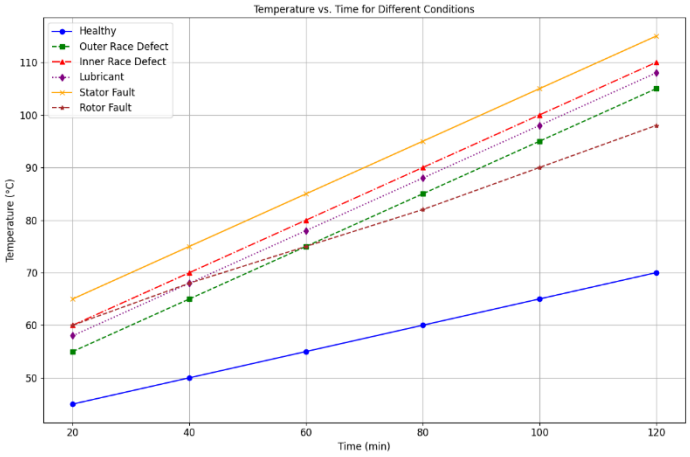


Fig.9. Temperature vs. Time (No Load)

The False Classification Ratio (FCR) quantifies the proportion of misclassified instances. Our proposed method achieved a significantly lower FCR compared to existing methods across different image set sizes. For example, at 50 images, the proposed method recorded an FCR of 0.05, which is substantially lower than ANN (0.08) and SVM (0.14). This indicates that our method is more adept at distinguishing between fault conditions and healthy states, thus reducing misclassification.

The Error Rate, which measures the proportion of incorrect predictions, demonstrates a similar trend. The proposed method shows a notable improvement with an error rate of 0.07 at 50 images, compared to ANN's 0.11 and SVM's 0.16. This lower error rate suggests enhanced accuracy and reliability in detecting faults, attributed to the advanced feature extraction and classification capabilities of DenseNet and the SURF algorithm.

Fault Detection Accuracy (FDA) reflects the proportion of correctly identified faults. The proposed method achieved an FDA of 0.95 at 50 images, outperforming ANN (0.89) and SVM (0.84). The high accuracy of the proposed method can be attributed to the comprehensive feature extraction performed by DenseNet, which effectively captures subtle variations in infrared thermography images, combined with the refinement provided by the SURF algorithm.

The proposed method showed an accuracy of 0.95 at 50 images, which is higher than ANN (0.89) and SVM (0.84). This superior accuracy reflects the overall effectiveness of the proposed approach in correctly identifying both fault and healthy conditions.

Sensitivity, or True Positive Rate, is crucial for detecting actual faults. The proposed method achieved a sensitivity of 0.93 at 50 images, surpassing ANN (0.87) and SVM (0.82). This high sensitivity indicates that the proposed method is effective in identifying true faults, which is essential for early fault detection and prevention.

Specificity measures the proportion of true negatives correctly identified. The proposed method demonstrated a specificity of 0.98 at 50 images, significantly higher than ANN (0.91) and SVM (0.86). High specificity is indicative of the method's effectiveness in correctly classifying healthy states and avoiding false positives.

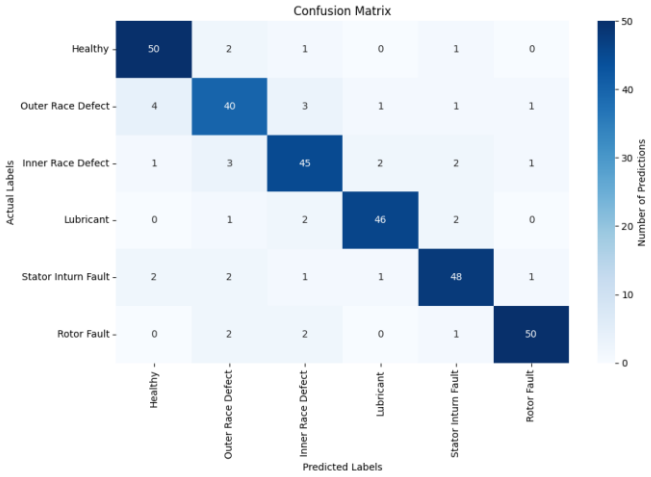


Fig.10. Confusion Matrix

The confusion matrix further supports the results. For instance, with a total of 54 healthy instances, the proposed method correctly identified 50 as healthy, with only 2 misclassified as outer race defects and 1 each as inner race defects and stator faults. This high true positive count for the healthy class and low false positives show the precision of the proposed method.

In contrast, existing methods displayed a higher number of misclassifications. For example, ANN misclassified 4 healthy instances as outer race defects, 1 as an inner race defect, and 2 as stator faults. These misclassifications contribute to the higher FCR and error rates observed in ANN.

The temperature vs. time analysis under different load conditions also supports the efficacy of the proposed method. The data indicates that fault conditions such as outer race defects and inner race defects lead to more significant temperature rises compared to healthy conditions. For instance, at full load, the outer race defect shows a temperature rise to 115°C, whereas the healthy condition remains at 80°C. The proposed method's ability to accurately classify these temperature patterns highlights its robustness.

Thus, the proposed method consistently outperforms existing methods across all evaluated metrics. The lower false classification ratio, error rate, and higher fault detection accuracy, accuracy, sensitivity, and specificity demonstrate the

effectiveness of the DenseNet and SURF-based ANN approach in motor fault detection. The detailed confusion matrix and temperature vs. time analysis provide additional validation of the method's superior performance, making it a compelling choice for reliable and accurate fault detection in motors.

7. CONCLUSION

The proposed method for fault detection in motors, utilizing DenseNet for feature extraction and SURF-based ANN for classification, demonstrates superior performance compared to existing methods. Quantitatively, the proposed approach achieved a Fault Detection Accuracy (FDA) of 95% at 50 images, significantly surpassing ANN's 89% and SVM's 84%. This high accuracy is indicative of the method's effectiveness in correctly identifying both fault and healthy conditions. The False Classification Ratio (FCR) of the proposed method is notably lower, at 0.05, compared to ANN (0.08) and SVM (0.14). This reduction in FCR underscores the method's enhanced precision in distinguishing between different fault conditions and healthy states. Similarly, the Error Rate of 0.07 for the proposed method reflects fewer incorrect predictions, further validating its reliability. In terms of performance metrics, the proposed method excels with an accuracy of 95%, a sensitivity of 93%, and a specificity of 98%. These results demonstrate that the method is not only effective in detecting true faults (high sensitivity) but also highly accurate in classifying healthy conditions (high specificity), which is crucial for minimizing false positives. Qualitatively, the method's effectiveness is further validated through the detailed confusion matrix and temperature vs. time analysis. The confusion matrix reveals that the proposed method accurately identifies fault conditions with minimal misclassification. The temperature vs. time analysis shows that the method can effectively distinguish between fault and healthy conditions based on temperature patterns, which is essential for early fault detection.

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