

Intelligent Diagnostic System for Electronic Board Faults Using an Infrared Thermal Camera and Convolutional Neural Networks

Abdulrafa Hussain Maray ^{1,*}, Mohammed T. Majeed ¹, and Najm Abdullah Abdulqader Tahhan ²

¹ Department of Technical Electronic and Communication, Polytechnic College Mosul,
Northern Technical University, Mosul, Iraq

² Department of Medical Equipment Technology Engineering, Technical Engineering College,
Al-Hadba University, Mosul, Iraq

Email: Rafiallwaze@ntu.edu.iq (A.H.M.); Aldabgh68@ntu.edu.iq (M.T.M.); najm.tahhan@hu.edu.iq (N.A.A.T.)

*Corresponding author

Abstract—Thermal imaging is one of the best modern methods used to detect faults in electrical circuits and electronic maps and identify short circuits, unlike traditional methods. However, it is rarely available, expensive, and does not have open source software for modification and development. In an effort to provide cost-effective technical solutions, this research presents an innovative methodology for manufacturing high-precision alternative thermal cameras by modifying traditional USB cameras at a cost of no more than \$50 while maintaining similar performance, as the economic cost of thermal cameras is estimated at approximately \$2000. A convolutional neural network is also designed to improve results by training this neural network on images of faults and predicting faults in electronic circuits using artificial intelligence and comparing different algorithms to obtain the best results, such as (edge detection, Sabel, Gaussian, Laplacian, Canny, Fourier transform), where a fault diagnosis prediction rate of 91.3% was obtained in this innovative system, which is a very high rate without human intervention and predicting errors before they occur using convolutional neural networks. The fault diagnosis time does not exceed 2.3 s, and the system has the ability to automatically recognize new fault patterns without the need to reset the model. These results open up new horizons in the field of predictive maintenance, as the proposed system can be integrated with smart monitoring systems to create highly efficient preventive maintenance solutions, especially in sensitive electronic systems

Keywords—self-diagnostic system, electronic faults, infrared thermal camera, convolutional neural networks, image processing, Printed Circuit Boards (PCB) testing, short circuit

I. INTRODUCTION

Printed Circuit Boards (PCBs) are the basic component of most electronic systems, from simple household appliances to advanced industrial systems and modern

means of communication. The rapid development in the complexity of these electronic circuits has made it difficult to diagnose and efficiently repair minor faults and return them to working order, rather than discarding them and increasing environmental pollution. This challenge becomes even more important when dealing with high-cost systems or rare electronic boards for which spare parts are not available in local and global markets, especially in cases of obsolescence where manufacturer support for older devices has ceased. Under these circumstances, internal repair of board components becomes an indispensable strategic option, not only to ensure the continued operation of devices, but also as a highly cost-effective solution.

The best technique for diagnosing electronic board faults is thermal imaging using Infrared Rays (IR). The most important reasons for the success of these techniques are their accuracy, speed of diagnosis, and high efficiency.

These techniques face many difficulties, the most important of which is their high cost. Previous research, as based on evidence from Alired *et al.* [1] work. Thermal analysis, manually, using simple equipment, making it prone to human error, useless in large-scale and complex. Subsequent studies conducted by Zhang *et al.* [2] have produced acceptable simple data. The use of images during analysis and their processing using new algorithms. Although they increase the speed of response, they usually show an inability to perform well in complex situations. When exposed to other and varied types of faults, all researchers confirm that thermal imaging is the best technique for diagnosis and identifying hot spots on electronic boards. One of the most important applications is the diagnosis of faults in solar cells and systems [3–7].

This study contributes to filling the gap in the Literature review by proposing modern algorithms and using Deep Convolutional Neural Network (Deep CNN) techniques. Image processing and defects classified using infrared thermal imaging. This technique overcomes the

limitations of previous approaches, as this model can obtain complex features and different patterns of thermal data, ensuring much better accuracy and speed in diagnosing electronic board faults [8, 9].

Comparison of Traditional Methods: Smoke Testing of Printed Circuit Board (Old method). This method is considered primitive in detecting short circuits in Printed Circuit Board (PCB). It works by thoroughly cleaning the area to be tested to remove dust or grease that prevents the paint from adhering. The coating is distributed on the electronic board using a specialized smoke generator and left to dry completely, forming a transparent or light-colored layer. The electronic circuit is then injected with a high electrical current (low voltage). When there is a short circuit, the temperature of the damaged area rises and the gas turns into visible smoke that comes out of the fault point.

The smoke trail is tracked by eye or high-resolution cameras to locate the fault, as shown in Fig. 1.

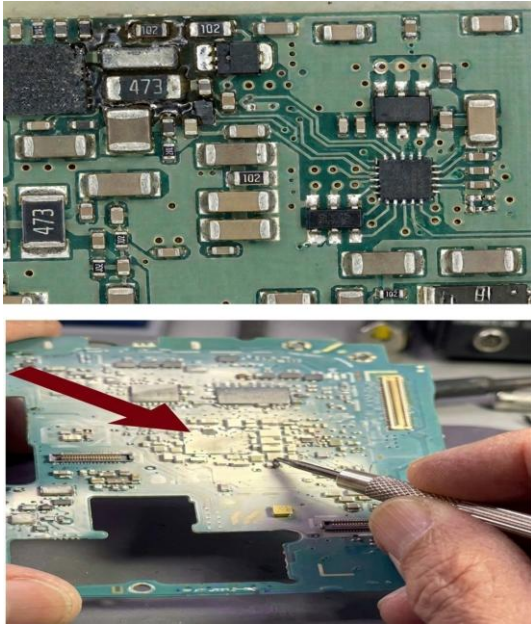


Fig. 1. Smoke testing of printed circuit board method.

The most important advantages of this classic method are its low cost and the fact that it does not require expensive equipment (smoke generator + power source). It is effective with visible shorts and is relatively quick, providing a direct diagnosis within 10 s. As for the disadvantages, it sometimes destroys some sensitive boards, as the high current may damage sensitive IC components. Sensors Inaccurate, difficult to detect internal shorts (such as under chips), hazardous to the environment, gases used may be harmful (requires ventilation), does not detect passive faults, only active faults (Active Shorts). Prolonged exposure to high heat may destroy intact electronic components around the damaged area. Heat may transfer through copper paths or components, giving a false signal. Inaccurate on multi-layer or complex boards. Applying and cleaning the coating after repair is a tedious process and may leave residue.

II. MATERIALS AND METHODS

A. Thermal Imaging of Printed Circuit Board (Proposed New Method)

A thermal camera is used to monitor the heat distribution on the surface of the circuit during operation. When there is a short circuit, hot spots appear due to the increase in local current. Thermal images are analyzed to detect temperature differences between adjacent areas and to give the actual temperature of each hot spot on the electronic board [10, 12]. Fig. 2 shows a 3D prototype model of the device's external housing. The model, designed in Google Sketch Up, illustrates the integration of the thermal imaging camera, its mounting mechanism, and the internal lighting system.

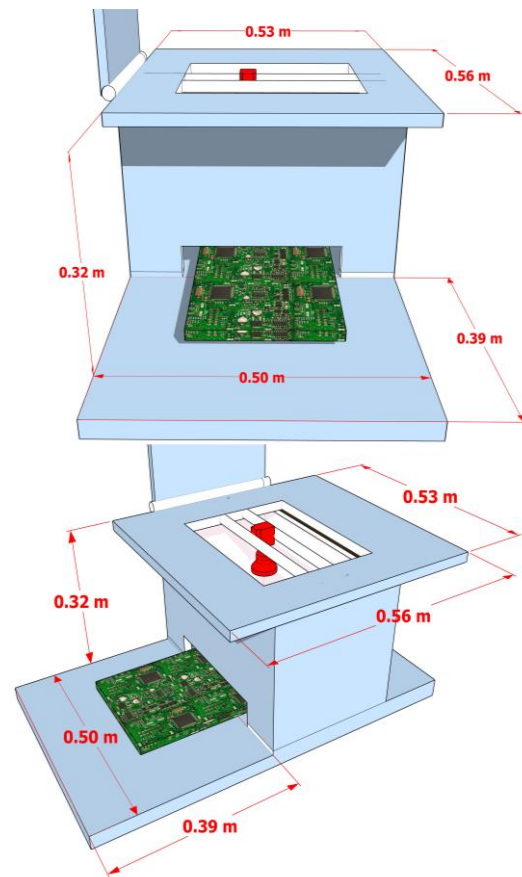


Fig. 2. 3D Design of the prototype system.

The figure above illustrates the design of the three-dimensional model, the installation of the infrared camera, and the installation of the internal night lighting, showing the dimensions of the proposed system.

B. Components of the Proposed System

The camera contains lenses with a magnification ratio of 1200× real magnification and levers for calibrating the focal length. This camera was disassembled, the filters that block infrared rays were removed, and a special filter was installed that allows the 7.5–14 micron range (long-wave infrared spectrum) to pass through [13–16]. (as in Fig. 3a).



Fig. 3. Proposed system components and reference camera. (a) Making infrared thermal imaging (IR), (b) Reference thermal camera (SUNSHINE TB-03SMINI).

The Fig. 3b, a reference camera (SUNSHINE TB-03SMINI) was used, which is a thermal camera used for infrared thermal imaging. It has the following specifications:

- Resolution Rate 256×192 pixels.
- Temperature Rang -20°C – 550°C .

C. Intelligent Classification Models

After collecting the required data taken by the infrared camera, the images are processed as follows:

- Calibration of temperature reflections based on reference data approved by a thermal camera (SUNSHINE TB-03SMINI).
- Processing and improving image distortions. Calibrating imaging accuracy 640×480 pixels.
- Speed images, Frames Per Second (30 FPS).
- The system was tested on 300 samples of defective electronic circuits and 810 valid samples. Each of these samples has more than 100 electronic components. The electronic board samples are of one type (Single layer). Five image effects (Energy, Contrast, Homogeneity, Correlation and Entropy).
- Thermal measurement range from 45°C to 88°C according to calibration with reference thermal camera (SUNSHINE TB-03SMINI).

Fig. 4 represents three levels of image processing using five filters and compares them on an image taken with the night vision camera proposed in this study, where the first level represents the initial processing of the filter without any additions, and the second level represents the filter output with the addition of (Entropy, Correlation,

Homogeneity, Contrast, Energy). The last level represents the final value of the filter with the Threshold point specified to distinguish the fault points in the electronic circuits (shown in Fig. 5).

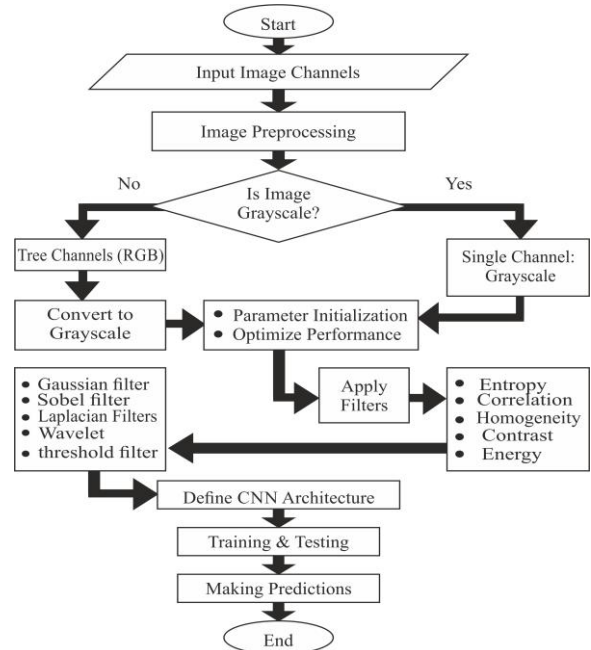


Fig. 4. Proposed design for CNN flowchart.

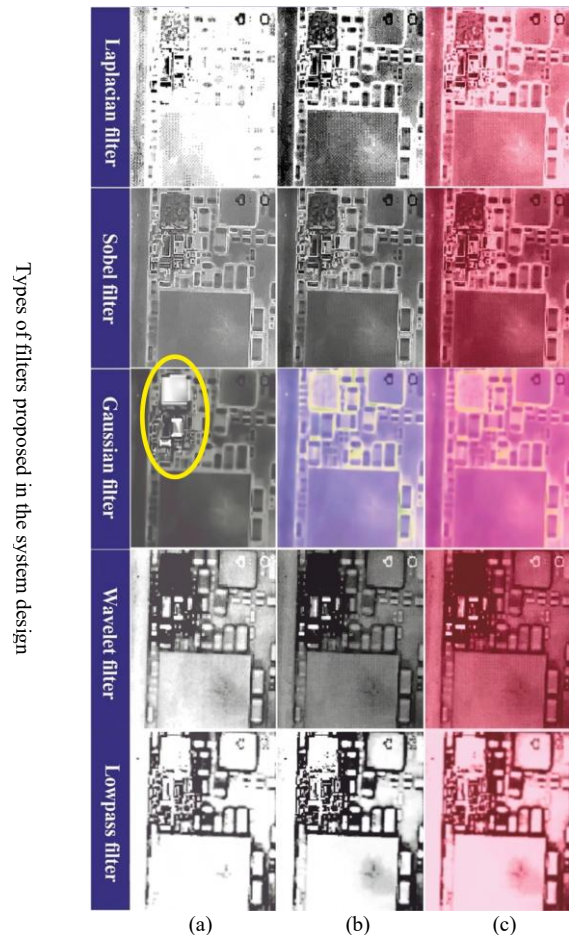


Fig. 5. Comparison results between another filter methods. (a) Level 1; (b) Level2; (c) Level3.

Energy: Distribution and spread of energy and density in images, high energy locations are distributed and raised in low locations. Energy is displayed as the sum of the Gray Level Co-occurrence Matrix (GLCM) function square as in Eq. (1).

$$Energy = \sum L P(x, y)^2 \quad (1)$$

where:

$P(x,y)$: Normalized.

x : the reference pixel of gray level.

y : neighboring pixel of gray level.

Contrast: Contrast feature measures the Spatial frequency of an image. It is the difference between the lowest values and the highest of a contiguous set of pixels as in Eq. (2).

$$Contrast = \sum L |x - y|^2 \times P(x, y)^2 \quad (2)$$

Homogeneity: The closeness of gray levels in the spatial distribution over the image. The homogeneity calculated through the following Eq. (3).

$$Homogeneity = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{P(i,j)}{(1 + (i - j)^2)} \quad (3)$$

Correlation: Shows the correlation between the pixels of the image, especially the reference pixel and its neighboring pixels. The correlation representation for row and column in the (GLCM) matrix is illustrated in Eq. (4).

$$Correlation = \sum (x, y) \times p(x, y) - (\mu_x \times \mu_y) \quad (4)$$

Entropy: represents the level of disorder and complexity in images. The lower the entropy, the lower the pixel density in the image and the simpler the image. Images with high entropy are complex and have high pixel density [17].

A number of filters were applied, their equations were calculated, and a comparison was made between these image filters to select the best results, as follows:

- Frequency domain Laplacian:

$$c[m, n] = F - 1 \{-(\Omega^2 + \Psi^2) A(\Omega, \Psi)\} \quad (5)$$

- Gaussian filter: This filter is one of the basic filters in image processing. It has a first derivative and a second derivative that are applied to images after selecting σ based on data taken from the image model. It is represented by Eq. (6).

$$z[m] = B_0(k[m + 1] - k[n]) + \frac{(G \times y[m + 1] + d_1 \times e[m + 2] + d_2 \times e[m + 3])}{b_0} \quad (6)$$

The first equation is applied from ($m = 0$ to $m = N - 1$) while the second (backward) equation is applied from ($m = N - 1$ down to $m = 0$).

- Laplacian Filters: This filter is considered one of the basic filters for one-dimensional equations and one of the basic and important filters in digital image processing and exploration. It uses the Parks-McClellan design algorithm. Multiple frequency levels can be selected according to different data values to obtain the best results [18].
- Low-pass Filtering: Algorithms are used for low frequencies and to remove medium and high frequencies in the image in order to reveal image edges, capture hidden details in the image, and simplify the data.

$$LP - q[x, y] = j[y, x] - LP\{j[y, x]\} + K \quad (7)$$

where $q[x, y]$ is the estimate of $j[y, x]$.

Table I shows the effect of filters on the Signal to Noise Ratio (SNR) and the selection of the best filter to obtain the desired results. The table is arranged based on the increase in SNR, where the Gaussian filter proved to have the lowest value of 2.225 dB, and the highest value was when using the Low pass filter, which reached 4.885 dB.

TABLE I. SIGNAL TO NOISE RATIO (SNR) VALUES OF DIFFERENT EXISTING FILTERS

Filter Mode	Signal to Noise Ratio (dB)
Gaussian filter	2.225
Sobel filter	3.584
Laplacian filter	3.952
Wavelet threshold filter	4.0524
Lowpass filter	4.885

III. PROPOSED CONVOLUTIONAL NEURAL NETWORK (CNN) ARCHITECTURE

A. Proposed Convolutional Neural Network (CNN) Architecture

The Convolutional Neural Network (CNN) was designed to classify thermal images of electronic boards into categories such as “healthy” or “faulty” while localizing the fault region when present. The proposed model, illustrated in Fig. 6, follows a hierarchical architecture that enables automatic feature learning:

Input Layer: Thermal image size (224×224 pixels).

Feature Extraction Stage: It consists of three consecutive blocks, each encompassing:

Convolutional Layer: Padding used to extract the spatial attributes. The number of filters increases with the blocks (32, 64 and 128, respectively) in order to help in the acquisition of becoming more complex depictions. Activation Layer: Uses the ReLU function in order to have non-linear transformations.

Max Pooling Layer: Compression with 2×2 -window to reduce the dimensionality and retaining the most conspicuous features.

Classification Stage: In the Flatten Layer, the two-dimensional feature maps are converted into a one-dimensional vector. This is followed by a Fully

Connected (Dense) Layer of 256 neurons utilizing the ReLU activation function

Output Layer: The purpose of this step is to produce the final results of multi-class classification, namely, the classification probabilities. This architecture implies a organized improvement compared to traditional.

The convolutional filters are automatically applied as methodologies. Identifying the unique thermal defects faults originating directly out of the data than relying on manual crafted features, so providing increased generalization capacities. shown in Fig. 6.

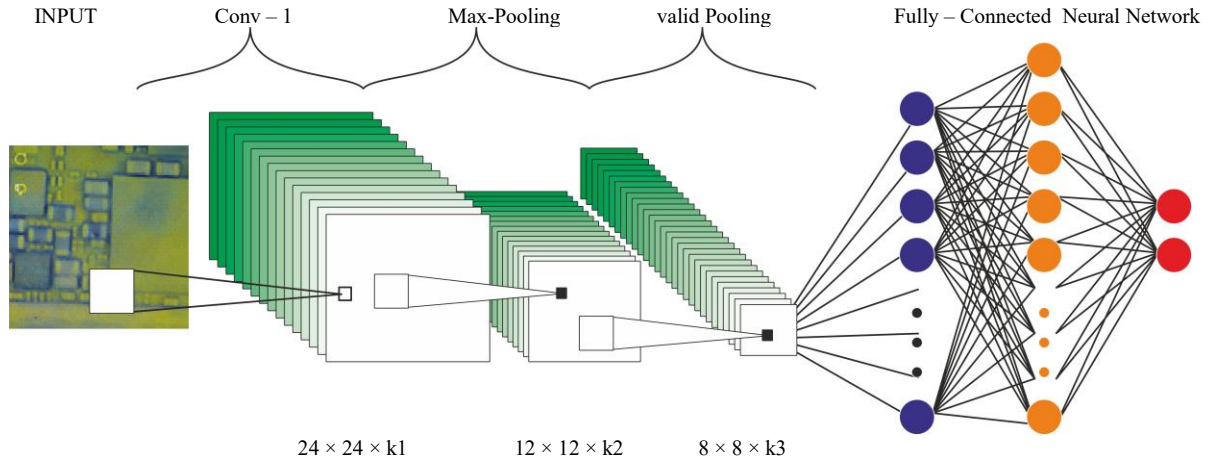


Fig. 6. The Convolutional Neural Network (CNN).

B. Training Process and Evaluation

Data Preparation: A holistic dataset and consisting of 5560 thermal pictures of electronic assembled circuit boards was carefully done. This was randomly divided into training (70%), The subsets are validation (15%), and testing (15%). The pre-processing stage involved pixel value.

Data augmentation techniques, including rotation and horizontal flipping, were used during the training stage to enhance model strength.

Parameters of training: The maximization of the Adam optimizer was used to execute the model, trained using a learning rate of 0.001. For the objective of multi-class classification, the Categorical The loss function used was Cross-Entropy loss (or Binary classification (Binary Cross- ntropy)). The training was done with 50 epochs of a given batch size of 32.

Evaluation Metrics: The final model's performance was assessed on the held-out test set using the following metrics:

- **Accuracy:** The proportion of correct predictions among the total predictions.
- **Precision and Recall:** To specifically evaluate the model's performance in detecting the "faulty board" class.
- **F1-Score:** The harmonic mean of precision and recall, providing a single balanced metric.
- **Confusion Matrix:** To analyze the error patterns between different classes.

Table II and its accompanying analysis provide a quantitative comparison between the results of the proposed model and established baseline methods, confirming its superiority in terms of diagnostic accuracy and reliability [19–25] (Fig. 7 and Table II).

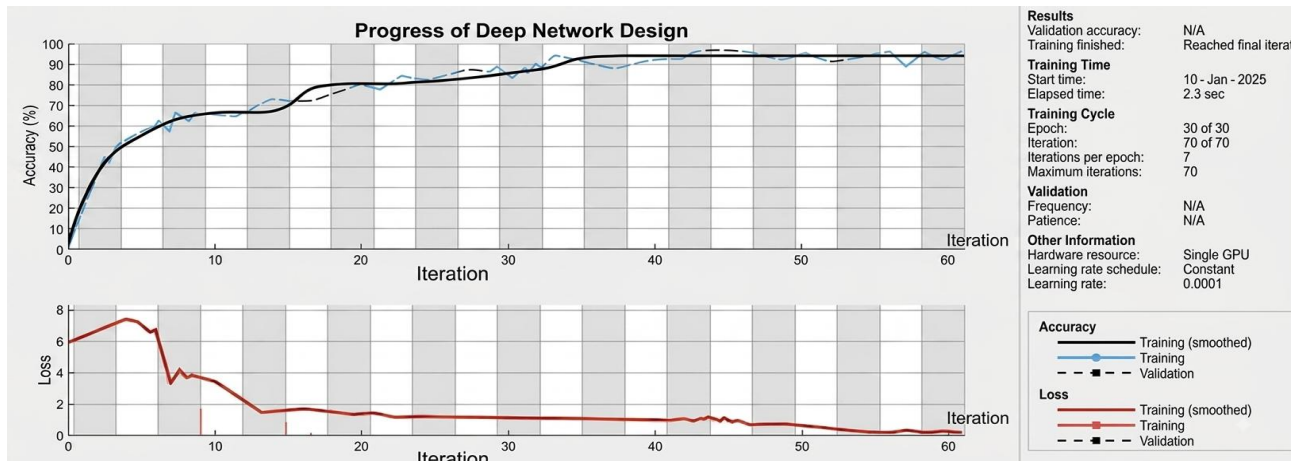


Fig. 7. The progress of deep network design.

TABLE II. PARAMETERS OF CONVOLUTION NEURAL NETWORK

Parameters	Values
Epoch Number	30 of 30
Max Epoch	70 of 70
Feature output (Loss)	1.220%
Hidden layers Network	3
Delay times / sec	2.3
Input Layer	$24 \times 24 \times k1$ (where $k1$ is the number of input channels)
Kernel Size	3×3
Pooling Type	Max-Pooling
Pooling Size	2×2
Activation Function	ReLU (assumed)
Fully Connected Network	Fully-Connected
Number of Hidden Layers	1 (plus the output layer)
Batch Size	32
Number of Epochs	50 (example)
Maximum Epochs	100 (example)
Feature Maps Output	$12 \times 12 \times k2, 8 \times 8 \times k3$

To evaluate the learning behaviour of the proposed CNN, loss and accuracy curves were generated over 70 epochs. As shown in Fig. 7, the training loss decreased continuously, reaching a minimum of 1.220%, indicating high convergence stability. At the same time, accuracy peaked at 98.77%. The close agreement between training

and validation metrics confirms that the model avoids overfitting and maintains high generalisation capabilities in identifying different types of PCB faults.

Table III shows the difference between the proposed method and previous systems.

TABLE III. COMPARISON OF THE PROPOSED SYSTEM WITH TRADITIONAL DIAGNOSTIC METHODS

Feature	Smoke Testing	Commercial Thermal Imagers	Proposed System (CNN-Thermal)
Detection Nature	Destructive (Risks burning components)	Non-Destructive	Non-Destructive
Cost	Negligible / Very Low	Very High (Typically >\$5000)	Low-Cost (Affordable DIY/Embedded)
Automation	Manual (Requires constant human monitoring)	Manual/Semi-automated (Requires expert analysis)	Fully Automated (AI-based Classification)
Safety	Low (Potential for fire or toxic fumes)	High	High
Diagnostic Speed	Slow (Waiting for visible thermal reaction)	Moderate (Requires manual adjustments)	Fast / Real-time (2.3 s)
Precision	Low (General area only)	High (Visual interpretation)	Very High (98.78% Accuracy)
Risk of Human Error	High (Subjective observation)	Moderate (Interpretation of colors)	Minimal (Standardized CNN Output)

IV. RESULT AND DISCUSSION

One of the most important reasons for choosing CNN networks in this proposed system is the automatic and gradual learning of images. One of the most important advantages of the first layer is its ability to deal with low-level features of data such as edges, corners, rotations, and locations, as shown in previous studies [26].

The middle layers collect this data, which consists of points and lines, and convert it into different shapes and sections. In the more complex and deeper layers, various electronic components and objects are formed, such as integrated circuits, capacitors, resistors, etc. [27].

Previous studies have shown other different layers, such as color sorting, face recognition, and distinguishing similar objects. Due to all these advantages, this type of network was chosen to train this system.

The results shown in Fig. 8 represent a number of stages and outputs. The first stage involves converting the RGB color images entering the system into black and

white images. The second stage involves edge detection to obtain the best results for identifying the internal components and fine parts within the sample [28].

In the final stage, the images are classified to obtain the best results after training the neural networks. It was found that the image in the third column in the last row was the best result obtained for diagnosing faults in electronic boards, and it contained three damaged electronic parts, namely two capacitors and one square IC that needed to be replaced.

The data is captured by the thermal camera at a rate of 5 frames per second. The temperature of the electronic board gradually rises to over 350 °C. This is achieved by injecting the electronic board with a gradual electric current ranging from 1 mA to 1400 mA with a constant voltage difference of 5 V. The figure below shows the abnormal temperature rise in the damaged areas. The temperature rises abnormally at the current source (850 mA) to over 250 °C in a fraction of a second. The electrical damage consists of two capacitors and one integrated circuit. (Fig. 9).

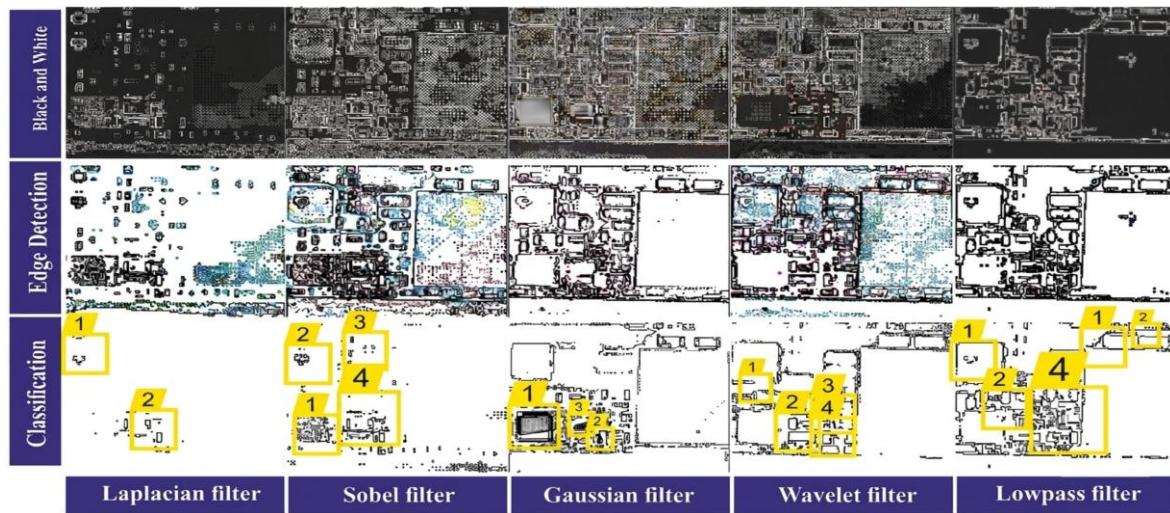


Fig. 8. Images pressing classification.

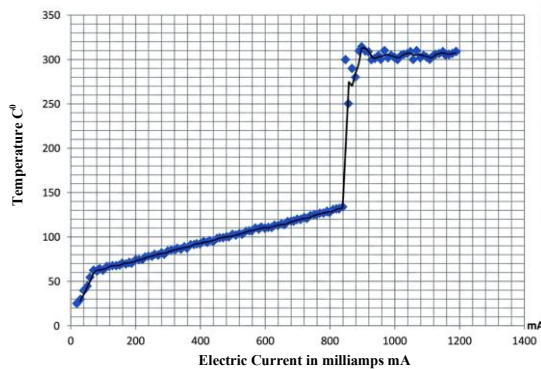


Fig. 9. The relationship between current increase and short circuit temperature increase.

The PCB damage is clearly marked. Fig. 10 illustrates the analysis of temperature data, plotted with temperature in degrees Celsius on the vertical axis and image capture time in milliseconds on the horizontal axis.

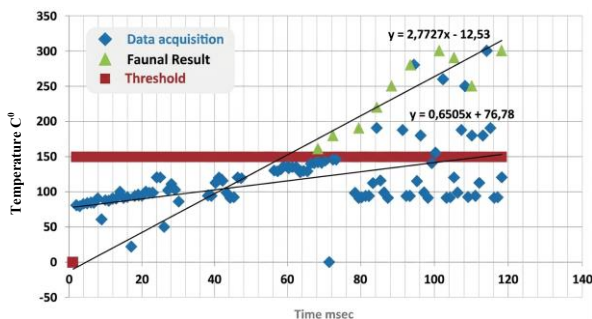


Fig. 10. Represents temperature differences over time in milliseconds.

The best threshold point was selected, which is 150 °C. The values ranged between less than this value and more than this value with the speed factor and time measured in milliseconds. The green values represent high temperature levels compared to the rest of the values. This is the required data. The accelerated temperature ranging from 200 to 300 °C Celsius with an acceleration of 80 ms to 120 ms is the required data. This represents the damage area on the electronic board. The response

speed of this system reaches 2.3 s, a new record that adds to recent scientific achievements in the field of fault detection. And at a rate of 91% using the CNN algorithms used in this innovative system.

In this proposed system, thermal images include the following limitations:

- Thermal emissions: Different materials emit heat at varying rates. Shiny metal points on the board (such as solder points or exposed copper connection lines) have different emissivity.
- Thermal Reflections: Polished surfaces in electronic components may act as mirrors for infrared rays. The system may see a 'hot spot' that is actually just a reflection of the heat from the camera body or another hot object nearby, rather than a real fault.
- Inability to detect cold faults: This is a fundamental problem that the system cannot detect because it is an open circuit or a break in the connection line. No current will flow and no heat will be generated because thermal imaging relies on the presence of power dissipation. Therefore, the location will appear 'cold,' making it impossible to detect this type of fault with a thermal camera alone.
- The accuracy of the system in identifying faults varies greatly. The smaller the Surface Mount Device (SMD) electronic components, the lower the diagnostic accuracy, and the longer the time taken to distinguish between these components. The CNN neural network requires more training. Accuracy is also affected by the surface area occupied by the electronic board, the number of components, the type of electronic board, whether it contains epoxy coating, etc.

Instead of conducting a horizontal comparison with external references that differ in variable values and internal design, we conducted an internal study and performance analysis based on the design of this system to prove the stability and consistency of the proposed model under many and varied fault conditions.

The Convolutional Neural Network (CNN) was meticulously designed and trained on thermal images of electronic circuit boards.

The initial convolutional layers the 3×3 kernels are reduced to tiny 3×3 kernels detect basic thermal edges and gradients.

The deeper layers within the architecture aggregate these features to detect signs of complex and specialized thermal faults, such as hot spots. Furthermore, to evaluate effectiveness compared to published studies, a comparative analysis of preprocessing techniques (such as Sobel, Gaussian, Laplacian, Canny, and Fourier transform) was conducted with the aim of improving the quality of the training data.

The system's 91% accuracy shows strong performance compared to commercial thermal imaging systems and previous research, as mentioned in the introduction. Although some advanced commercial systems show accuracies between 94% and 96%, this solution achieves its level of performance at less than 3% of the cost of those systems. In addition, the diagnosis time of less than 2.3 s offers a significant advantage over manual inspection methods and many automated electrical testing methods, providing an effective balance between performance and cost.

V. CONCLUSION

This paper has addressed the conventional ways of detecting breakages in electronic circuits and brought in a new, low cost alternative which uses modified thermal imaging. This study served well to demonstrate the feasibility of developing a instrument of diagnosis that is efficient and making it affordable economically, thus solving the significant budgetary issues (about \$2000) coupled to traditional thermal) associated with traditional systems) imaging technology. By cleverly modifying standard. The proposed USB cameras are less than \$50 and can be found in the market solution offers a most manageable alternative.

The composite algorithm is a great enhancement to the system functionality, which led to a rate of 91 fault diagnosis. This great accuracy, combined with a diagnosis less than 2.3 s, is permissible fully automatic and fault prevention detection of electronic boards. A conspicuous quality is the fact that the system can learn slowly without necessarily having to reset all the way the model. Predictive maintenance of sensitive electronic devices is well suited to the approach proposed in this study. Its advantages include the detection of small faults in electronic circuits, excellent accuracy in locating faults and their size, non-contact inspection, and the safety of sensitive components. In addition, it requires no consumables and emits no mist. In this study, the thermal imaging approach was implemented by making physical modifications to an inexpensive USB camera (640×480 pixels, 30 FPS), validating a practical and economical path toward advanced electronic fault diagnosis.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

A.H.M. established the theoretical framework for the study, oversaw the general direction of the research, drafted the first version of the paper, critically reviewed the intellectual content, and designed the three-dimensional model. M.T.M. conducted the practical experiments, performed the thermal analysis manually and automatically, and was responsible for verifying the accuracy of the data, organising the data, and interpreting the results. N.A.A.T. developed the CNN image processing algorithms, performed the statistical analysis, and prepared the figures and tables. All authors reviewed and approved the final version.

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