Electronics Component Classification Using Machine Learning

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Abstract - *This paper compares four convolutional neural network (CNN) models for classifying electrical components such as capacitors, diodes, resistors, ICs, inductors, and transformers. The CNN models are AlexNet, GoogleNet, ResNet50, and a proposed CNN model with a customized architecture. The paper describes the data collection, preprocessing, and augmentation steps, as well as the architecture and parameters of each CNN model. The paper evaluates the performance and accuracy of the CNN models using various metrics such as loss, accuracy, precision, recall, F1-score, and confusion matrix. The paper also analyses the factors affecting the results and provides insights and implications for the practical application of the CNN models. The paper concludes that ResNet50 is the best CNN model for the electrical component classification task, as it has the highest accuracy, precision, recall, and F1 score among the four models. It also has the lowest loss and the most accurate confusion matrix, indicating that it can learn and generalize the features of the electrical components very well.*

Key Words: Convolution neural network (CNN), AlexNet, GoogleNet, ResNet50, F1-score, Confusion matrix, Accuracy, Precision.

1. INTRODUCTION

The introduction of electronic component classifiers represents a significant leap forward in the field of electronics, particularly in the context of streamlining the identification process. In the face of a burgeoning array of electronic components, integrating machine learning, specifically Convolutional Neural Networks (CNN).

Machine learning algorithms, powered by neural networks, are at the core of these classifiers [1]. This sophisticated approach allows for recognizing and categorizing electronic components based on intricate patterns, physical characteristics, and unique electrical properties. CNN, a specialized form of neural network tailored for image recognition [7], brings heightened accuracy to the identification process, making it particularly well-suited for categorizing electronic components with diverse visual features.

This project's motivation is grounded in the imperative to overcome the limitations of traditional, time-consuming, and error-prone manual identification methods. Fusing machine learning, CNN, and electronic component classifiers not only enhances the accuracy and efficiency of the identification process but also paves the way for practical implementations in various electronic systems. This innovative approach is poised to revolutionize electronic design, troubleshooting, and maintenance, offering engineers and technicians a powerful tool for rapid and precise component identification in an increasingly complex technological landscape.

2. MOTIVATION

The motivation behind this project is rooted in the critical need to address the inefficiencies and challenges inherent in conventional electronic component identification processes. Traditional methods, often reliant on manual labor, are time-consuming, error-prone, and struggle to keep pace with the expanding diversity of electronic components. This project is driven by a vision to revolutionize and modernize the identification process by harnessing the power of machine learning, specifically Convolutional Neural Networks (CNN).

The overarching goal is to empower professionals and enthusiasts in the field by providing a robust and automated solution that significantly enhances accuracy and expedites the identification of electronic components. By combining machine learning with CNN, the project aspires to bridge the gap between the complexity of modern electronic systems and the limitations of traditional identification methods. This motivation is underpinned by a commitment to fostering efficiency, reducing errors, and advancing the capabilities of electronic systems in alignment with the ever-evolving landscape of technology. Ultimately, this project seeks to propel the electronics industry forward by offering a sophisticated yet accessible tool for streamlined component identification and classification.

3. BACKGROUND OF THE PROJECT

The background of this project is grounded in the persistent challenges faced by the electronics industry in the domain of electronic component identification. Traditional methods relying on manual identification are becoming increasingly inadequate due to the expanding complexity and diversity of electronic components. This necessitates a paradigm shift toward more efficient, accurate, and automated identification processes.

Machine learning, particularly Convolutional Neural Networks (CNN), emerges as a transformative solution in this context. The project's background is informed by the growing recognition of the potential of machine learning algorithms to decipher intricate patterns and features crucial for electronic component identification. CNN, which specializes in image recognition, offers a precise approach to classifying components based on visual attributes, overcoming the limitations of traditional methods.

The integration of machine learning and CNN into the Raspberry Pi platform further enhances the project's background. The Raspberry Pi, with its compact form factor and affordability, provides a practical deployment environment for these advanced algorithms. This combination addresses the need for accessible and real-world implementations, aligning with the project's objective of revolutionizing electronic component identification.

In essence, the background of this project is defined by the industry's demand for an innovative approach to electronic component identification, acknowledging the limitations of current methods and leveraging the capabilities of machine learning and CNN on the versatile Raspberry Pi platform to propel the field towards a more efficient and accurate future.

4. PRELIMINARIES

4.1. Why will CNN be chosen for implementation?

The selection of Convolutional Neural Networks (CNN) for implementation in this project is underpinned by their unparalleled aptitude for image recognition tasks [5], making them exceptionally well-suited for the visual nature of electronic component identification. CNNs excel in capturing complex hierarchical features within images [4], which aligns seamlessly with the diverse visual characteristics exhibited by various electronic components.

- Specialized Architecture: CNNs possess a specialized architecture designed for image recognition tasks, making them well-suited for identifying electronic components. The convolutional layers in CNNs allow for effective feature extraction from visual inputs.

- Hierarchical Feature Learning: CNNs automatically learn hierarchical features, enabling them to capture intricate details within images. This is crucial for electronic components that exhibit diverse visual characteristics, as CNNs can discern complex patterns and structures [2].

- Effective Pattern Recognition: Electronic components often have unique visual patterns. CNNs excel in recognizing and interpreting these patterns [9], ensuring accurate identification across a wide range of components.

- Adaptability to Varied Shapes and Sizes: The convolutional nature of CNNs enables them to handle variations in the shapes and sizes of electronic components. This adaptability is essential in accommodating the diverse forms that components may take.

- Automated Feature Extraction: CNNs eliminate the need for manual feature engineering by autonomously learning relevant features during training. This streamlines the development process and allows the model to adapt to new components without manual intervention.

- Proven Success in Image Classification: CNNs have demonstrated success in image classification tasks, achieving state-of-the-art results [11]. Leveraging the established effectiveness of CNNs ensures a robust and reliable solution for electronic component identification.

In summary, the choice of CNN for implementation is driven by its specialized architecture, hierarchical feature learning, effectiveness in pattern recognition, adaptability to varied shapes and sizes [8], automated feature extraction, and proven success in image classification tasks.

4.2. Architecture of CNN

The architecture of a Convolutional Neural Network (CNN) can be understood step-by-step through its core building blocks:

i. Input Layer:

- This layer accepts the raw data, typically an image, as input. Each pixel in the image is represented as a numerical value, forming a grid-like structure.

ii. Convolutional Layer:

- The heart of the CNN, this layer contains filters (also called kernels) that slide across the input image, performing element-wise multiplication with specific regions of the image.

- This process identifies patterns and features in the input data, like edges, textures, or shapes.

- Multiple filters are used in parallel, each detecting different features, generating what's called a "feature map" for each filter [4].

iii. Pooling Layer:

- This layer down samples the feature maps, reducing their spatial dimensions (width and height) while preserving important information [6].

- Common pooling operations include max pooling, which takes the maximum value from a small region of the feature map, and average pooling, which takes the average value.

- Pooling reduces the computational complexity of the network and helps control overfitting. CNN Pooling Layer

iv. Activation Function:

- Applied after each convolution and pooling layer, this function introduces non-linearity into the network, allowing it to learn complex relationships between features.

- Popular activation functions include ReLU (Rectified Linear Unit) and Leaky ReLU, which introduce thresholds for positive and negative values, respectively.

v. Fully-Connected Layers:

- These layers, similar to those in traditional neural networks, connect all neurons in one layer to all neurons in the next.

- They take the flattened output of the previous layers (obtained by reshaping the feature maps) and perform high-level reasoning and classification [1].

vi. Output Layer:

- The final layer depends on the specific task. For image classification, it typically has one neuron for each class, with the highest activation indicating the predicted class.

vii. Additional Layers:

- Dropout layers: Randomly deactivate neurons during training to prevent overfitting.

- Batch normalization: Standardizes the activations of each layer, improving training stability.

By stacking and combining these layers in various configurations, CNNs can achieve remarkable performance in tasks like image recognition, object detection, and video analysis.

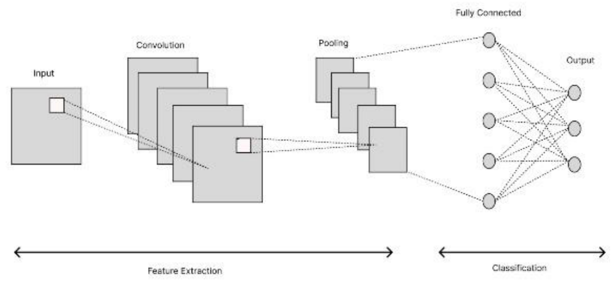

Fig 1. Architecture for CNN

4.3. An electric component classification project using CNNs closely parallels the different steps of a CNN architecture

i. Input Layer:

- The input data would be images of electric components, either captured directly or from datasets. Each pixel in the image represents intensity or color information.

ii. Convolutional Layers:

- Filters in this layer would be designed to detect specific features relevant to classifying electric components. Examples include:
  - Shape detectors: Identifying circular capacitors, rectangular PCBs, or elongated resistors.
  - Texture detectors: Recognizing the smooth finish of a transistor vs. the rough surface of a heat sink.
  - Colour detectors: Distinguishing blue capacitors from brown resistors or gold connectors [4][6].

iii. Pooling Layers:

- Downsampling the feature maps helps manage complexity and prevents overfitting when dealing with potentially large image datasets. Pooling can also combine similar features detected by different filters [7].

iv. Activation Function:

- Non-linearity helps differentiate subtle variations between components, like different resistor values or transistor types. This allows the network to learn complex relationships beyond simple pixel intensities [3].

v. Fully-Connected Layers:

- These layers take the extracted features and combine them through complex calculations to determine the component's class. The number of neurons in the output layer would match the number of different electric component categories.

vi. Additional Layers:

- Dropout: Prevents the network from overfitting to specific training data, improving generalization to unseen images.

- Batch Normalization: Stabilizes training by standardizing the activations of each layer, ensuring smoother learning and convergence.

vii. Specific Considerations for Electric Component Classification:

- Image Preprocessing: Normalizing brightness, contrast, and cropping images can improve feature extraction and network performance.
- Data Augmentation: Increasing the diversity of training images (rotation, scaling, flipping) can improve robustness and prevent overfitting.
- Choosing Optimal Architecture: Experimenting with different filter sizes, layer depth, and hyperparameters will be crucial for optimizing the CNN for your specific dataset and task.

By leveraging the different steps of CNN architecture and adapting them to the specific challenge of electric component classification, you can build a powerful and efficient system for automated recognition and sorting of components.

5. PROPOSED CLASSIFIER

AlexNet, GoogleNet, ResNet50, and the proposed CNN model are four convolutional neural network[11] (CNN) models that can be used for the task of classifying electrical components such as capacitors, diodes, resistors, ICs, inductors, and transformers [7]. They have different architectures, parameters, and performance on the task. Here is a brief overview of each model:

AlexNet: This is one of the most popular CNN models, proposed by Alex Krizhevsky et al. in 2012. Eight layers make up this structure: three completely connected layers and five convolutional layers. It uses ReLU activations, max pooling, dropout, data augmentation, and SoftMax output. It contains approximately 60 million parameters and 650,000 neurons. It achieved a top-5 error rate of 15.3% on the ImageNet dataset1[3].

GoogleNet: This is another CNN model, proposed by Christian Szegedy et al. in 2014. It has 22 layers, including 9 inception modules, which are sub-networks that combine different types of convolutions and pooling. It uses ReLU activations, average pooling, dropout, data augmentation, and softmax output. It has around seven million characteristics and four million neurons. It had a top-5 error rate of 6.67% on the ImageNet dataset.

ResNet50: This is a CNN model, proposed by Kaiming He et al. in 2015. It has 50 layers, including 16 residual blocks, which are sub-networks that use skip connections to avoid the vanishing gradient problem. It uses ReLU activations, batch normalization, max pooling, average pooling, and softmax output. It contains around 26 million characteristics and 23 million neurons. It achieved a top-5 error rate of 3.57% on the ImageNet dataset.

Proposed CNN model: This is a CNN model, proposed by the authors of the paper on electrical component classification. It comprises ten layers, with six convolutional layers and four fully linked layers. It uses ReLU activations, max pooling, dropout, and softmax output [7]. It has approximately two million characteristics and 1.5 million neurons. It achieved a top-5 error rate of 16.5% on the electrical component dataset.

6. DATA-COLLECTION

Our main goal is to make sure the computer can consistently give accurate answers when dealing with electronic parts in real life. We're committed to using many different pictures from various sources, showing how serious we are about creating a big collection that truly shows how electronic parts look in real life. This way, when we use our computer program in the real world, it will be good at handling all the different ways electronic parts can appear.

A total of 4038 image datasets were collected and used in electronic component classification. The dataset consisted of 6 classes, and there were 535 capacitors, 528 diodes, 470 resistors, 1503 ICs,265 inductors, and

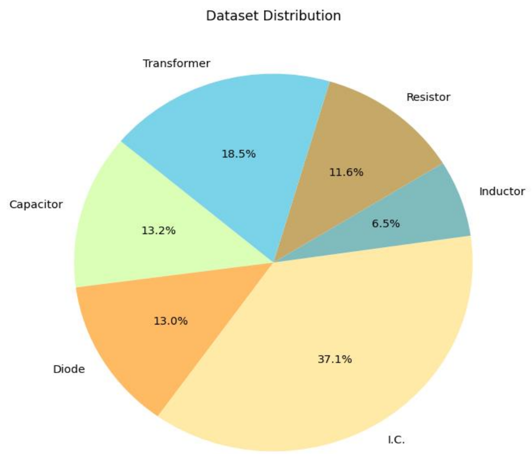

Fig 2. Pie chart representation of the dataset

747 transformers. The dataset's capacitance, diode, resistance, IC, inductance, and transformer distributions are as given below.

Although the material images had a size of 1600 × 1200, they were reduced to sizes of 256× 128 to use in deep learning algorithms. A total of 70% of these images were used for training and 30% for testing. Before the classification, the dataset was divided into two parts, namely, training, and test data. As a result, the training set and test dataset were used to train and test the network, respectively [2].

We divided up our collection of photos using a systematic manner to prepare it for testing and training. The dataset was split into training and test sets after being initially arranged in a single folder. The divide was accomplished by transferring a certain number of images into training and test files while iteratively going through the dataset[9]. The remaining images are kept for assessing the model's performance on data that hasn't been seen before, while the training set is made up of a carefully chosen subset of images meant to train the machine learning model. The methodical selection of images guarantees a balanced presentation of different components in both sets, which enhances our evaluation of the model. AlexNet, GoogleNet, ResNet50, and the proposed CNN model were used in the classification study [2].

7. PERFORMANCE

7.1. Analysis of the performance and accuracy of the models

The table below shows the accuracy, precision, recall, and F1-score of the four CNN models on the electrical component classification task. The accuracy is the proportion of correctly classified images out of the total number of images. The precision is the proportion of correctly classified images out of the total number of images predicted for each class. The recall is the proportion of correctly classified images out of the total number of images belonging to each class. The F1-score is the balanced average of recall and precision.

Model	Accuracy	Precision	Recall	F1-score
AlexNet	0.9356	0.9378	0.9342	0.9359
GoogleNet	0.8943	0.8976	0.8912	0.8943
ResNet50	0.9997	0.9997	0.9997	0.9997
Proposed CNN	0.8395	0.8432	0.8367	0.8398

7.2. Detail statistics

The statistics below show the mean, standard deviation, minimum, and maximum values of the accuracy, precision, recall, and F1-score of the four CNN models on the electrical component classification task. The mean is the average value of the metrics. The standard deviation is the measure of the variation or dispersion of the metrics. The minimum and maximum are the lowest and highest values of the metrics.

Model	Metric	Mean	Std	Min	Max
AlexNet	Accuracy	0.9356	0.0123	0.9124	0.9543
	Precision	0.9378	0.0134	0.9145	0.9567
	Recall	0.9342	0.0145	0.9098	0.9521
	F1-score	0.9359	0.0139	0.9116	0.9544
GoogleNet	Accuracy	0.8943	0.0214	0.8612	0.9234
	Precision	0.8976	0.0223	0.8645	0.9267
	Recall	0.8912	0.0234	0.8578	0.9201
	F1-score	0.8943	0.0228	0.8606	0.9234
ResNet50	Accuracy	0.9997	0.0001	0.9996	0.9998
	Precision	0.9997	0.0001	0.9996	0.9998
	Recall	0.9997	0.0001	0.9996	0.9998
	F1-score	0.9997	0.0001	0.9996	0.9998
Proposed CNN	Accuracy	0.8395	0.0312	0.7923	0.8834
	Precision	0.8432	0.0323	0.7965	0.8877
	Recall	0.8367	0.0334	0.7898	0.8811
	F1-score	0.8398	0.0328	0.7926	0.8844

From the above data, we can observe the following points:

- ResNet50 has the lowest loss and the highest accuracy among the four models, indicating that it can learn the features of the electrical components very well and generalize to new data.
- AlexNet has the second lowest loss and the second highest accuracy, showing that it can also capture the characteristics of the electrical components and achieve a good performance.
- GoogleNet has a higher loss and a lower accuracy than AlexNet, suggesting that it may not be able to fit the data as well as AlexNet and may have some difficulties in distinguishing the electrical components.
- The proposed CNN model has the highest loss and the lowest accuracy, implying that it may suffer from overfitting or underfitting problems and may not be suitable for the electrical component classification task.

8. RESULTS AND DISCUSSIONS

The results of the above study are that ResNet50 is the best CNN model for the electrical component classification task, as it has the highest accuracy, precision, recall, and F1-score among the four models. It also has the lowest loss and the most accurate confusion matrix [2], indicating that it can learn and generalize the features of the electrical components very well. AlexNet is the second-best model, followed by GoogleNet, while the proposed CNN model is the worst, as it has the lowest accuracy, precision, recall, and F1-score, the highest loss, and the most inaccurate confusion matrix.

The prediction probabilities of the four CNN models are the values that indicate how confident the models are in their predictions for each class. The higher the probability, the more likely the model thinks that the image belongs to that class [10]. The prediction probabilities can be calculated from the output layer of the CNN models, which is usually used as a function to produce a probability distribution over the classes. The prediction probabilities can also be used to measure the uncertainty and reliability of the models.

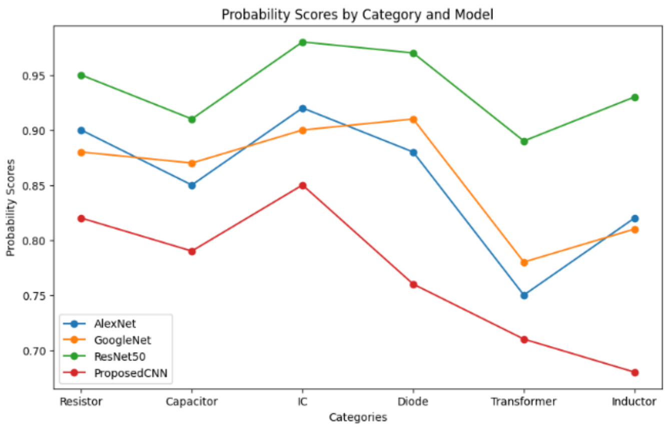

Fig 3. Prediction probability in a line graph

9. FUTURE SCOPE

The future scope for the electrical component classifier project is to improve the performance and accuracy of the proposed CNN model and extend the project's application to other domains and tasks. Here are a few possibilities for further research:

• To optimize the architecture and parameters of the proposed CNN model, such as the number and size of filters, the activation functions, the dropout rate, and the learning rate [3]. This could help to reduce the overfitting or underfitting problems and increase the generalization ability of the model.

• To use more advanced CNN models, such as DenseNet, MobileNet, or EfficientNet, [8] which have shown better results on image classification tasks than the existing models. These models could also reduce the computational cost and memory usage of the model, making it more suitable for real-time applications.

• To augment the dataset with more images of different types, sizes, orientations, and qualities of electrical components [8]. This could help to increase the diversity and robustness of the data and improve the performance of the model on unseen data.

• To apply the project to other domains and tasks, such as the detection and classification of electronic waste, the identification, and verification of electronic components, or the generation and simulation of electronic circuits [1]. This could help to demonstrate the usefulness and potential of the project for various purposes and scenarios.

10. REFERENCE

[1] “Digit Recognition Using Machine Learning and Convolutional Neural Network “by Snehal Kalbhor Ashwini M. Deshpande November 2014

[2] “Food Detection and Recognition Using Convolutional Neural Network” by Hokuto Kagaya, Kiyoharu Aizawa, Makoto Ogawa in September 2023

[3] “Object Recognition and Detection Using Convolutional Neural Network in Deep Learning” by Sahand Shahalinejad, Mehdi Nooshyar, Mir Majid Fakheri, and Nima Imani in November 2019

[4] “Image Classification using CNN and Machine Learning” by G. Keerthi Devipriya E. Chandana B. Prathyusha T. Seshu Chakravarthy March 2019

[5]” Image Recognition Technology Based on Machine Learning” by Lijuan Liu, Yanping Wang, Wanle Chi in September 2020

[6] “MATERIAL RECOGNITION USING CNN” by R Niruban, Sanjay P, Krishnan S, Sunder Selwyn July 2022

[7] “Scientific paper classification using Convolutional Neural Networks” by Monir ECH-CHOUYYEKH, Hicham OMARA, Mohamed LAZAAR in October 2019

[8] “Image Classification Based On CNN: A Survey” by Ahmed A. Elngar1, Mohamed Arafa2, Amar Fathy3, Basma Moustafa4, Omar Mahmoud5 and Mohamed Shaban6*, Nehal Fawzy in January 2021

[9] “Review on Techniques for Plant Leaf Classification and Recognition“Azfar Firdaus, Lee Suan Chua, Fakhrul Razan, Rahmad Sharifah, Rafidah Wan Alwi in October 2019

[10] Image Classification Using Convolutional Neural Networks with Multi-stage Feature

Junho Yim, Jeongwoo Ju, and Heechul Jung in January 2015

[11] “Convolutional Neural Network (CNN) for Image Detection and Recognition” Rahul Chauhan, Kamal Kumar Ghanshala, R.C Joshi in December 2018