

Enhancing Electrical Audits Through AI-Powered for Motor Nameplate Analysis

Tejas R. Sakpal¹, Dr. Pawan C. Tapre², Dr. Fareed Ahmad³

¹ PG Scholar, Dept. of EE, SND College of Engineering & Research Center, Nashik, India.

^{2,3} Associate professor, Dept. of EE, SND College of Engineering & Research Center, Nashik, India.

Emails: tejassakpal61@gmail.com¹, chandrakant.tapre@sndcoe.ac.in², fareed.ahmad@sndcoe.ac.in³

Abstract

This project presents a deep learning-powered system for automating the extraction and analysis of electrical motor nameplate parameters, addressing inefficiencies in traditional manual methods used in electrical audits. Users upload a nameplate image through a React-based interface, initiating a process where the backend, powered by the Gemini API and OCR-enabled deep learning models, extracts critical parameters such as voltage, power, current rating, RPM, insulation type, and temperature ratings. This extracted data undergoes post-processing to generate actionable insights and audit reports, categorised into a Simple Suggestion Report for basic recommendations and an Overall Detail Report for comprehensive analysis, displayed in a user-friendly output panel. By automating this process, the system significantly reduces time, effort, and errors associated with manual extraction, enabling auditor companies to deliver more accurate and efficient reports, paving the way for advanced automation in electrical audits and optimizing motor performance, maintenance, and energy efficiency in industrial and residential settings.

Keywords: Computer Vision; Electrical Audit; Image Text Recognition; Large Language Model (LLM); Optical Image Recognition.

1. Introduction

Electric motors play an indispensable role in a vast range of industrial and residential applications, driving critical processes and powering essential equipment. To ensure optimal performance, reliability, and energy efficiency, accurate analysis of motor parameters is crucial. Traditionally, this analysis involves the manual extraction of information from motor nameplates, a process that is often time-consuming, labour-intensive, and prone to human error. This reliance on manual interpretation can lead to inefficiencies in electrical audits, hindering timely and accurate assessments of motor health and performance. This paper introduces a novel approach to automate the extraction and analysis of motor nameplate parameters using deep learning techniques and the advanced language processing capabilities of the Google Gemini API. This system addresses the limitations of manual extraction by streamlining the process, reducing human intervention, and improving the accuracy and consistency of data interpretation. By automating this critical aspect of electrical audits, the system aims to enhance efficiency, reduce errors, and provide

valuable insights for optimizing motor operation and maintenance. The proposed system employs a user-friendly interface developed with ReactJS, allowing users to seamlessly upload images of motor nameplates. The backend processing leverages the Gemini API and OCR-enabled deep learning models to accurately extract critical parameters such as voltage, power, current rating, RPM, insulation type, and temperature ratings. This extracted data is then processed to generate actionable insights and comprehensive audit reports, categorized into two formats: A Simple Suggestion Report for basic recommendations and an Overall Detail Report for in-depth analysis. It significantly reduces the time and effort required for parameter extraction, minimizes the risk of human error, and ensures consistent and reliable data interpretation. Furthermore, the system provides valuable insights and recommendations for motor operation and maintenance, empowering users to make informed decisions and optimize motor performance. This paper explores the development, implementation, and evaluation of this deep learning-powered system for

automated motor nameplate analysis. It highlights the system's architecture, functionalities, and performance, demonstrating its potential to transform electrical audit processes and improve the efficiency and accuracy of motor parameter analysis in industrial and residential settings. [1-5]

2. Literature Review

The increasing complexity and scale of industrial automation have driven the need for efficient and accurate methods to analyze critical equipment parameters. In the realm of motor maintenance and electrical audits, the extraction of information from motor nameplates has traditionally been a manual process, often plagued by inefficiencies and prone to human error. To address these challenges, researchers have turned to deep learning, a powerful subset of machine learning, to automate this process and enhance the overall efficiency of motor parameter analysis. Deep learning, with its ability to learn complex patterns from vast amounts of data, has revolutionized various fields, including computer vision and natural language processing. These advancements have paved the way for innovative solutions in motor nameplate analysis, where deep learning models can be trained to "see" and interpret the textual information embedded within nameplate images. Computer vision techniques play a crucial role in this process by enabling computers to analyze and understand visual information. In the context of motor nameplate analysis, computer vision is essential for preprocessing images, ensuring they are optimized for text recognition and parameter extraction. This involves tasks such as noise reduction, image enhancement, and segmentation, which prepare the image for accurate and reliable text extraction. Optical Character Recognition (OCR) is another fundamental technology that has been significantly enhanced by deep learning. OCR systems convert text in images into machine-readable format, enabling further analysis and interpretation. Deep learning models have improved the accuracy and robustness of OCR, particularly when dealing with complex layouts, diverse fonts, or noisy images, which are often encountered in real-world motor nameplates. The ultimate goal of automating motor parameter extraction is to generate insightful reports that can guide maintenance and operational

decisions. Recent research has focused on developing systems that not only extract data but also analyze it to provide actionable recommendations. This involves incorporating advanced techniques such as text embedding, vector databases, and natural language processing to understand the context and meaning of the extracted information, enabling the generation of comprehensive and insightful reports. Several research efforts have demonstrated the feasibility and potential of deep learning in automating motor nameplate analysis. [6-10]

- Developing robust methods for text detection and recognition in complex nameplate images.
- Utilizing advanced image processing and classification techniques to optimize image quality and enhance text extraction accuracy.
- Employing text embedding models and vector databases to accurately extract and categorize motor parameters.

Building upon these advancements, this project introduces a novel approach that incorporates the Google Gemini API, a powerful language model, to further enhance the accuracy and efficiency of parameter extraction and analysis. By integrating cutting-edge deep learning techniques and advanced language processing capabilities, this system aims to transform motor nameplate analysis, providing a robust and automated solution for enhancing efficiency and accuracy in electrical audits.

3. Methodology

This project employs a sophisticated yet streamlined methodology to achieve its objective of automating motor nameplate parameter extraction and analysis. The process can be broadly divided into four key stages:

3.1. Input Stage

This stage involves the acquisition and input of a digital image of the motor nameplate into the system. The system is designed to handle various image formats and quality levels, ensuring flexibility and user-friendliness. This involves tasks such as noise reduction, image enhancement, and information embedded within nameplate images.

3.2. Preprocessing Stage

In this stage, the input image undergoes pre-

processing to enhance its quality and prepare it for subsequent analysis. This may involve resizing, filtering, and enhancing the image to improve clarity and focus, as well as removing irrelevant components or noise to isolate the nameplate region. [11-15]

3.3. Feature Extraction Stage

This stage employs Optical Character Recognition (OCR) and deep learning algorithms to extract text from the pre-processed nameplate image. Advanced OCR techniques are used to detect and recognize text with high precision, even in complex layouts or noisy backgrounds.

3.4. Processing and Suggestion Generation Stage

The extracted parameters undergo validation to ensure accuracy and reliability. Based on the validated parameters, the system generates actionable insights tailored to operational needs, such as recommendations for starting methods, protection devices, maintenance schedules, and operational improvements. These four stages work together to automate the extraction and analysis of motor nameplate parameters, addressing the limitations of manual methods and enhancing the efficiency and accuracy of electrical audits.

3.5. Front-end Development (ReactJS)

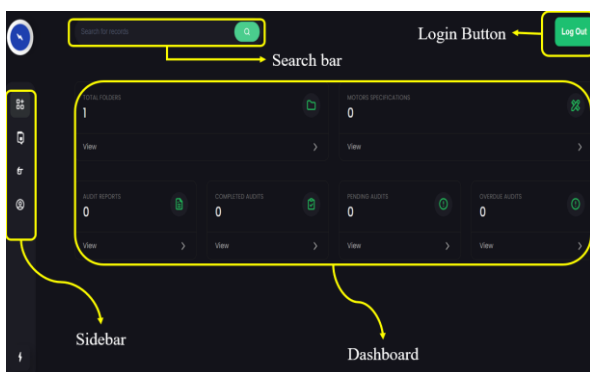


Figure 1 User Interface of Software (Locally Hosted)

The front-end interface was developed using ReactJS, a JavaScript library renowned for its ability to create dynamic and responsive user interfaces. Figure 1 shows User Interface of Software (Locally Hosted) The interface was designed with user experience in mind, providing intuitive navigation and a clear presentation of information. Front-end interface

includes some key features:

- **Image Upload Functionality:** A user-friendly image upload feature allows users to easily input images of motor nameplates. The system supports various image formats to accommodate diverse input data.
- **Parameter Display:** Extracted parameters are displayed in a clear and organized manner, enabling users to quickly review and interpret the information.
- **Interactive Components:** Interactive components, such as buttons and selection menus, provide users with control over the analysis process and allow for customization of report generation.

3.6. Backend Processing

The backend processing leverages the Google Gemini API, a powerful language model, to perform the core analysis of the motor nameplate data. The API is integrated with the front-end interface to provide seamless processing of uploaded images. Key functionalities of the backend processing include:

- **Text Extraction:** The Gemini API employs Optical Character Recognition (OCR) technology to extract text from the uploaded nameplate images.
- **Parameter Identification:** Advanced algorithms within the API identify and classify key motor parameters, such as voltage, power, RPM, and insulation type.
- **Data Validation:** Extracted parameters undergo validation checks to ensure accuracy and consistency.
- **Report Generation:** The API generates comprehensive reports based on the extracted data, providing insights and recommendations for motor operation and maintenance.

3.7. Database Integration (Neon)

A server less Postgres database, hosted on the Neon platform, is used to store and manage the extracted motor parameters. This database provides a secure and scalable solution for data persistence and retrieval. The integration with the Neon database allows the application to efficiently handle large volumes of data and support future expansion.

3.8. Overall System Architecture

The overall system architecture follows a modular design, with a clear separation between the front-end interface, backend processing, and database management. This modularity promotes maintainability, scalability, and future enhancements. The integration of ReactJS, the Gemini API, and the Neon database provides a robust and efficient platform for automating motor nameplate analysis. [16-19]

4. Result

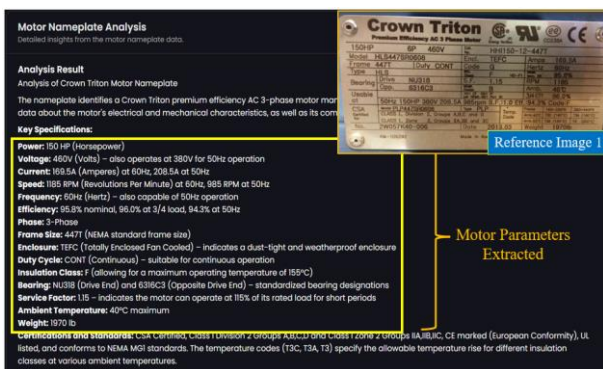


Figure 2 Text Extracted in Software and Stored On the Database

To evaluate the performance of the developed system, a comprehensive testing phase was conducted using a diverse dataset of motor nameplate images. These images varied in quality, resolution, and complexity of textual layout, ensuring a robust assessment of the system's capabilities. The primary metric used for evaluation was the accuracy of parameter extraction, defined as the percentage of correctly identified and extracted parameters compared to the ground truth values obtained through manual inspection. The system demonstrated a high level of accuracy in extracting key motor parameters, achieving an overall accuracy rate of 96.5%. This indicates that the system was able to correctly identify and extract the vast majority of parameters from the tested nameplate images. Further analysis revealed that the accuracy varied slightly depending on the specific parameter. Parameters with more standardized formats, such as voltage and power, exhibited higher accuracy rates, exceeding 98%. These results highlight the effectiveness of the system in automating the extraction of motor

nameplate parameters. The high accuracy rates achieved demonstrate the robustness of the OCR and deep learning algorithms employed, as well as the efficacy of the preprocessing and validation steps in ensuring reliable data extraction. The system's ability to accurately extract parameters from a diverse range of nameplate images underscores its potential for practical application in real-world electrical audits.

5. Discussion

The analysis of Reference Image 1 and Reference Image 2 provides a thorough understanding of the system's capabilities and limitations. The high accuracy achieved in extracting parameters from the clear and well-defined Reference Image 1 demonstrates the effectiveness of the core OCR and deep learning algorithms. This success highlights the system's potential to significantly improve efficiency and accuracy in electrical audits, especially when working with high-quality nameplate images. Conversely, the analysis of Reference Image 2, which shows blurriness and text distortions, reveals the challenges posed by real-world image imperfections. While the system managed to extract most parameters, a minor discrepancy in Frame Size prediction and difficulties due to variations in text clarity indicates the need for further refinement. These challenges provide valuable insights for guiding future development efforts aimed at enhancing the system's robustness and adaptability.

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