Optimizing Industrial Etching Processes for PCB Manufacturing: Real-Time Temperature Control Using VGG-Based Transfer Learning

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Abstract. Accurate temperature control in Printed Circuit Board (PCB) manufacturing is essential for maintaining high-quality etching results. Automated monitoring using machine vision and deep learning offers an effective approach for this task. This study investigated a feature-based transfer learning technique for classifying temperature readiness in infrared images of the etching process. The captured dataset containing 470 'Production-Ready' and 480 'Not-Ready' infrared images of the etchant tank was utilized. Pre-trained Visual Geometry Group (VGG) Convolutional Neural Network (CNN) models, specifically VGG16 and VGG19, were employed to extract discriminative features from these images. Logistic Regression (LR) classifiers were then trained on these features to classify the infrared images. The performance of the VGG16-LR and VGG19-LR pipelines was evaluated on training, validation, and test sets using a 60:20:20 split. While both pipelines achieved 100% accuracy on the training sets, the VGG19 pipeline showed exceptional performance, achieving a validation accuracy of 95%, and a test accuracy of 99%. The VGG16 pipeline also demonstrated robust performance, achieving 96% accuracy on both the validation and test sets. Considering the dimensions and the overall efficiency of the pipeline, it was determined that the VGG19-LR model was appropriate for the captured dataset. The high accuracy indicates that transfer learning is suitable for categorizing temperature fluctuation in infrared thermography, as opposed to training a deep neural network from scratch. Computer vision and deep learning provide automated and precise temperature management during the etching process, leading to enhanced efficiency in PCB manufacturing.

Keywords: Temperature Control, PCB Manufacturing, Transfer Learning, Infrared Imaging, Feature Extraction, Convolutional Neural Networks (CNN)

1 Introduction

PCB production is the meticulous elimination of undesired copper to form circuit layouts, a task accomplished through chemical etching. Ferric chloride ($FeCl3$) is frequently employed for this specific purpose. It is essential to maintain the etchant at an ideal temperature to achieve high-quality etching results [1]. However, managing the temperature of the etchant is challenging since variations can impact both the speed and quality of the etching process [2].

Typically, etchant tanks are heated at the start of the week and maintained at a warm temperature of 45°C during the workweek. During production shifts, fluctuations in temperature can cause irregularities in the etching process, leading to flaws such as excessive or insufficient etching. Moreover, conventional temperature sensors that rely on physical contact are frequently inadequate in this situation as they can be intrusive and may not yield precise measurements due to restricted coverage and the possibility of being tainted by the etching chemicals [3].

Fig. 1 illustrates a complex production setup with two primary production lines of a medium-sized chemical etching company, labelled 'Etching production line 1' and 'Etching production line 2', and three etching tanks. Tank no.1 is primarily connected to production line 1 but also has a secondary connection to production line 2. Tank no.2 is centrally connected to both production lines. Tank no.3 primarily serves production line 2 while maintaining a backup link to production line 1. This configuration ensures that each production line can consistently access the etching solution, allowing for operational redundancy and flexibility, thus maintaining continuous production even if one tank is offline for maintenance or refilling.

However, this setup also complicates the task of maintaining the ideal temperature. With multiple tanks connected to different production lines, variations in demand and usage can cause temperature fluctuations within each tank. These fluctuations can lead to inconsistent etching quality if the tanks are not properly monitored and controlled. Additionally, the backup connections between tanks and production lines introduce further complexity, as the temperature in one tank can be influenced by the operational state of another. Therefore, achieving and maintaining an optimal temperature in this production setup requires advanced monitoring and control strategies to account for the dynamic interactions between tanks and production lines.

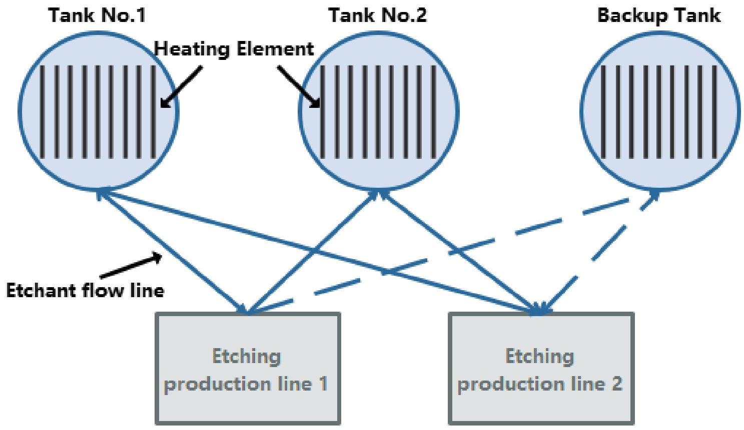


Fig. 1. Company's chemical etching line set up

In order to tackle these difficulties, it is imperative to employ sophisticated monitoring methods such as machine vision and infrared imaging[4, 5]. These technologies offer a more precise and non-intrusive way to gauge and manage the temperature of the etchant tanks. While conventional temperature sensors often fall short in this context, machine vision and infrared imaging can provide comprehensive and accurate temperature data, ensuring consistent etching quality. Although these methods are not yet widely adopted in the industry, they represent a promising approach to overcoming the current challenges associated with temperature monitoring in PCB production. Additionally, advancements in computing technology, such as CNN have significantly improved in performance and capability for processing and extracting features from images. Utilizing CNN for defect identification in manufacturing applications has shown significant promise in improving quality control and efficiency, such as in additive manufacturing [6], surface defect detection [7, 8], and semiconductor wafer defect detection [9].

To construct a resilient model with dependable decision-making capabilities, a conventional approach based on CNN necessitates a substantial amount of input data, which frequently entails a lengthy training period. Weimer et al. [10] introduced a CNN based system for automatic feature extraction. The program is trained using a dataset of 1.3 million images and the training process takes 24 hours. An issue commonly encountered with classic CNN models, which are developed from scratch, is the lack of sufficient labeled data necessary to develop a strong algorithm. Therefore, researchers predominantly turn to transfer learning as a means of transferring information between other domains, which presents a promising approach to address the aforementioned issue [11]. These models excel at extracting features due to their training on a huge database [12]. For example, Singh et al. developed an efficient image-based framework using a pre-trained CNN (ResNet-101) and multi-class Support Vector Machine (SVM) for detecting surface defects in manufacturing, requiring minimal training data and computational resources. Damacharla et al. [13] demonstrated the utilization of transfer learning models, specifically U-Net combined with ResNet and DenseNet, to extract features from images for the purpose of detecting fault locations in steel sheets. Huangpeng et al. [14] proposed an alternative approach for detecting defects on steel surfaces. In those research, AlexNet and VGG models were used to extract features and incorporated deep sparse coding to enhance memory usage and computational performance. There are researchers that exploited the use of pre-trained VGGNet models for feature extraction, followed by SVM [15] or k-Nearest Neighbour (kNN) [16] classifier, which can significantly improve classification accuracy. It could be seen that machine learning classifiers do pair up well with the CNN-based feature extraction method. Nevertheless, very limited study has been done on the real-time, fine control of temperature for chemical etching process. However, it is crucial to acknowledge that domain differences with different models can impact the success of transfer learning. To mitigate this, the domains used in this project are carefully selected to ensure similarity. Although the pre-trained VGGNet models were originally trained on general image databases, their robust feature extraction capabilities are leveraged to handle infrared images.

This study aims to tackle the challenges associated with the accurate measurement and control of etching fluid temperatures in PCB manufacturing by evaluating the efficacy of different VGG pre-trained CNN models with the LR model in classifying infrared images for optimised large industrial etching temperature control. By focusing on the thermal characteristics and temperature patterns in these infrared images, transfer learning can be effectively applied. This approach enhances the model's performance in temperature monitoring applications, reducing the need for extensive labeled data specific to the infrared domain.

2 Method

The experimental setup depicted in Fig. 2 consists of a chemical etching process combined with a real-time infrared sensor monitoring system. The primary components include:

1. A tank containing the etching solution, ferric chloride, utilized in the PCB manufacturing process.
2. The tank is connected to an etching chamber that belongs to production line 1, where the actual etching of the metal plates occurs.
3. Xenics Gobi+ infrared sensor utilizes an uncooled microbolometer detector with a resolution of 640 x 480 pixels and frame speeds of up to 60 Hz, is positioned to monitor the temperature of Tank No. 1.
4. The infrared sensor is connected to a data logging system that captures and processes the temperature image in real-time.

This setup employs machine vision and infrared imaging techniques to ensure precise temperature control of the etching solution, enhancing the consistency and quality of the etching process.

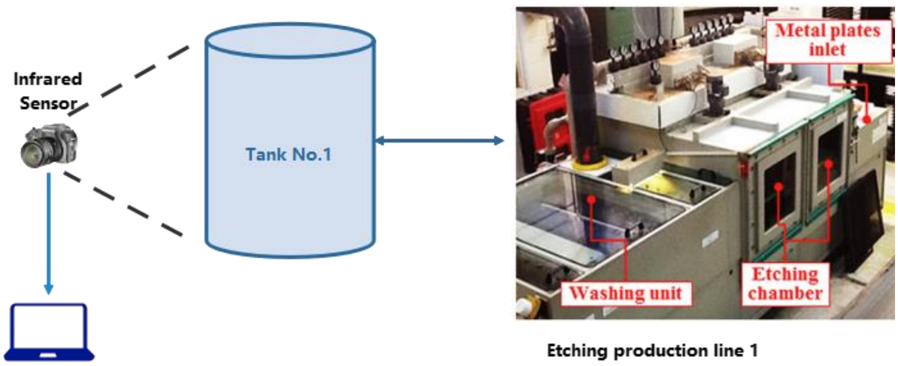
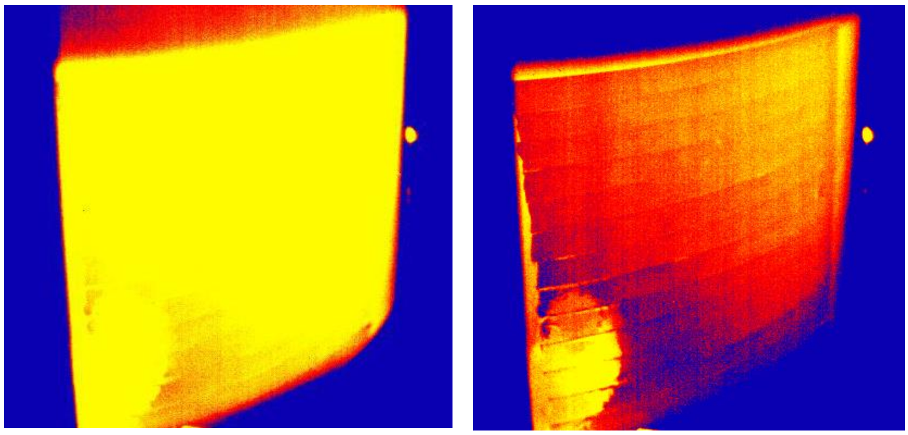


Fig. 2. Schematic of the experimental Setup

During eight hours of operation, the system captured 4,200 images. In this study, the sample size was reduced to 950 images, which were randomly selected from the larger dataset to ensure a representative sample. Each image was downsized to dimensions of 224 by 224 pixels to ensure compatibility with the pre-trained models. This resizing facilitates consistent feature extraction across all images, aligning with the input requirements of the VGGNet models, which were originally trained on images of this size. The dataset is classified into two categories: Production-Ready and Not-Ready as exemplified in Fig. 3 which displays sample infrared images representing these two groups. The dataset was partitioned using a 60:20:20 hold-out cross-validation procedure for the purposes of training, validation, and testing, respectively.



Production-Ready Not-Ready

Fig. 3. Sample infrared image of Production-Ready, Not-Ready

The process of extracting features from infrared images was carried out using pre-trained VGG architectures, specifically VGG16 and VGG19, with 16 and 19 layers respectively. These models belong to the VGGNet family of designs, known for their simplicity and effectiveness in handling deep learning tasks. VGG models use a series of convolutional layers followed by fully connected layers, which allow for deep feature extraction. The fully connected layers in the VGG models were removed to enable the extraction of high-level features. The extracted features were then utilized to build a LR classifier with the purpose of differentiating between the two temperature classifications: ‘Production-Ready’ and ‘Not-Ready’.

The performance assessment of the classification pipeline was carried out using metrics such as accuracy, precision, recall, and F1 score. The assessments were conducted using the Spyder Integrated Development Environment (IDE) with Python version 3.9. The pre-trained VGG16 and VGG19 models were acquired using the Keras and TensorFlow libraries, and the LR classifier was constructed using the sklearn package. In this specific investigation, the LR model is utilized with its default hyperparameters.

3 Results and discussion

The bar charts in Fig. 4 illustrates the classification accuracy of two VGG architectures (VGG16 and VGG19) when combined with the LR classifier. The accuracy is assessed by evaluating performance on training, validation, and test datasets. The VGG16-LR pipeline exhibited a perfect training accuracy of 100%, suggesting an exceptional alignment with the training data. The validation accuracy, however, reduced to 96%, indicating a minor case of overfitting as the performance on the validation set was slightly lower. The test accuracy closely matched the validation accuracy at 96%, indicating

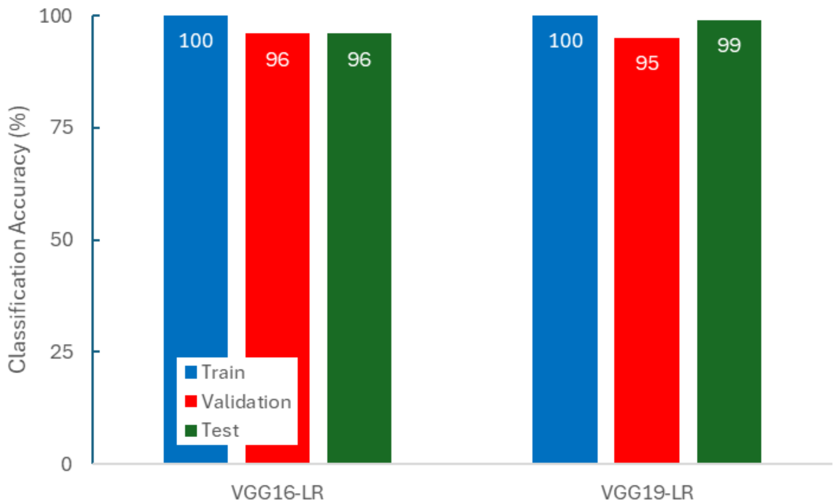


Fig. 4. Evaluated pipelines performance on detecting the etchant temperature conditions

consistent performance on separate data, albeit with a slight decrease compared to the training accuracy.

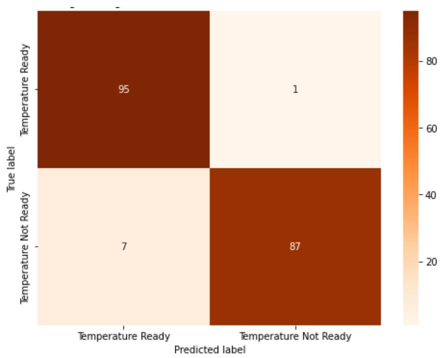
Similarly, the VGG19-LR pipeline obtained a perfect training accuracy of 100%, much as VGG16. The validation accuracy of VGG19 was marginally lower, standing at 95%, suggesting a modest overfitting problem like the VGG16. Nevertheless, VGG19 had a superior test accuracy of 99%, indicating a greater ability to generalize to unfamiliar data in comparison to VGG16.

The comparative findings suggest that both VGG16 and VGG19, when combined with the LR classifiers, provide excellent accuracy in classifying various datasets. However, VGG19-LR exhibits somewhat superior performance in generalizing to the test data.

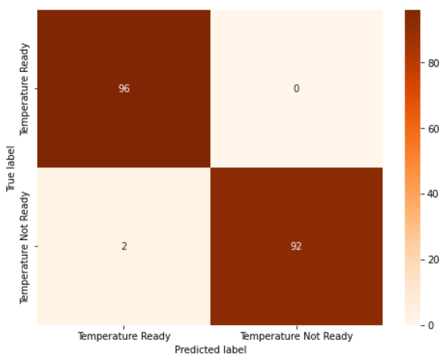
The confusion matrices for the VGG16 and VGG19 models combined with LR classifiers are shown in Fig. 5, which provide a comparative evaluation of their performance in classifying temperature readiness.

The VGG16-LR pipeline performs well but shows slightly more misclassifications. It correctly classifies 95 ‘Production-Ready’ and 87 ‘Not-Ready’ instances. However, it has one false positive and seven false negatives, indicating occasional misclassification of temperature states. This could lead to more frequent interruptions in the production process due to incorrect temperature status predictions, resulting in increased production downtime. Specifically, a false positive might cause an unnecessary halt in production, while false negatives could result in continuing production with suboptimal temperatures, potentially affecting the quality of the etched products.

In contrast, the VGG19-LR pipeline demonstrates superior performance, with 96 correct ‘Production-Ready’ classifications and 92 correct ‘Not-Ready’ classifications. It has a minimal error rate, with only two instances of ‘Production-Ready’ misclassified as ‘Not -Ready’ and no false positives. This high level of accuracy and precision suggests that VGG19-LR is highly reliable for real-time temperature classification, ensuring minimal errors in a production environment.



VGG16-LR



VGG19-LR

Fig. 5. Confusion Matrix of the VGG16 and VGG19 pipelines on the test dataset.

Comparatively, VGG19-LR demonstrates better overall performance and reliability than VGG16-LR. The higher accuracy and fewer misclassifications make VGG19-LR a more robust choice for ensuring precise temperature control in the etching process. The lower false negative rate in VGG19-LR minimizes the risk of proceeding with production when the temperature is not actually ready, thereby enhancing both efficiency and safety in the manufacturing process.

4 Conclusion

This study explored the use of VGG architectures in conjunction with the LR classifier to classify temperature readiness in industrial chemical etching applications. A comparative analysis was conducted on the performance of VGG16 and VGG19 models in accurately detecting temperature conditions from infrared images.

The VGG19 pipeline demonstrated the highest overall accuracy and the best ability to generalize to new data, particularly excelling in distinguishing between 'Production-Ready' and 'Not-Ready' temperatures. The VGG16 pipeline also showed strong performance, though it was slightly less accurate than the VGG19 pipeline in classifying temperature readiness. However, the perfect training accuracy of both pipelines raises a potential concern for overfitting, where the models may be memorizing the training data rather than learning generalizable features.

To address this concern, further investigation should include thorough validation and testing using separate datasets to evaluate the models' performance. Additionally, employing techniques such as regularization, dropout, and data augmentation will help mitigate overfitting and ensure that the models generalize well to new, unseen data. These steps will enhance the robustness and reliability of the temperature monitoring system, ultimately contributing to more accurate and efficient manufacturing processes.

In conclusion, this study highlights the potential of using advanced feature-based transfer learning techniques to improve the precision and reliability of temperature control in etching processes, thereby enhancing the efficiency and consistency of PCB production. Future research could explore optimizing the hyperparameters of the classifier, integrating other machine learning models, and extending this approach to different types of manufacturing processes. Additionally, investigating the long-term stability and performance of these models in continuous production environments could provide further insights into their practical applications and potential improvements.

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