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Design and Implementation of AI Machine Vision Inspection System with Multi-Optical Images for OLED Film Manufacturing

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Abstract

Machine vision technology is one of the main areas of rapid development in the modern world and is becoming increasingly important in various industries. This innovative technology uses the fusion of computer vision and artificial intelligence to process and analyze visual information, enabling the development of automated inspection systems and the automation of processes. In particular, machine vision technology is playing an increasingly important role in OLED film production and quality control. Currently, OLED film production is mainly based on visual inspection, but this method has various problems. It is labor-intensive and relies on humans, which limits the accuracy and consistency of the inspection. It is also difficult to identify defective elements with irregular shapes or sizes. To overcome these issues and revolutionize the field of OLED film production and quality control, we propose an OLED Film Inspection Architecture with Machine vision. This architecture utilizes advanced cameras and sensors to analyze the surface of OLED films in detail and automatically identify defective elements. In addition, by integrating multiple optical systems and AI deep learning algorithms, it can perform accurate inspections under various lighting conditions and detect defects in real time. By utilizing these advanced technologies, quality control and production efficiency can be greatly improved, which is expected to drive innovation in OLED film production. This research provides a high level of technical content and provides a bright outlook for the future of machine vision technology in the industrial field.

Index Terms—Machine vision, Automated Inspection System, Multi-Optical System

I. Introduction

In the modern world, technological advancements and innovations are occurring rapidly, and machine vision technology is gaining traction in various applications. Machine vision is a technology that combines computer vision and artificial intelligence technology to process and analyze visual information, and it is playing an innovative role in various fields such as automobile manufacturing, food inspection and packaging processes, and medical fields. These applications emphasize that machine vision technology is essential for modern industries to remain competitive and provide better products and services. Especially in the field of organic light emitting diodes (OLED) film production and quality control, there is an urgent need to adopt machine vision technology. Currently, the OLED film production process is mainly based on visual inspection, which is an important process for defect detection and quality control [1]. However, visual inspection is highly labor-intensive and relies on humans, which limits its accuracy and consistency. It also involves the subjective judgment of the inspector, depending on the size or shape of the object being inspected. This makes it difficult to detect defective elements with increased production or irregular shapes.

OLED Film Inspection Architecture with Machine vision is a general concept, and the idea generation process to materialize it is as follows [2]. Introduce a technology that utilizes a multi-optical system to precisely analyze the appearance of OLED film. This technology is one of the key factors that makes it possible to take pictures considering the characteristics of OLED film and to take pictures of nonreflective products. From the captured image data, detectable defective items are selected through classification and segmentation. This enables automatic classification and identification of inspection targets. Good and bad data learning: Based on the selected data, good and bad data are learned to recognize defect patterns. A 2:1 ratio of good and bad data is selected to learn and classify various features and patterns. By utilizing deep learning algorithms, defective patterns are identified with high accuracy and implemented for real-time inspection. Through this idea generation process, OLED Film Inspection
Architecture with Machine vision is expected to significantly improve quality control and production efficiency.

The composition of this paper as follows. Section 1 is the introduction, which describes the background and need of the research, and Section 2 introduces Machine vision, Automated Inspection, and Multi-Optical for this research. Section 3 describes the structure and process of the proposed model. Section 4 describes the image data, model implementation, and quantitative evaluation of the proposed model. Finally section 5 summarizes the conclusion and proposal models and describes future research plans.

II. Related Work

A. Machine Vision

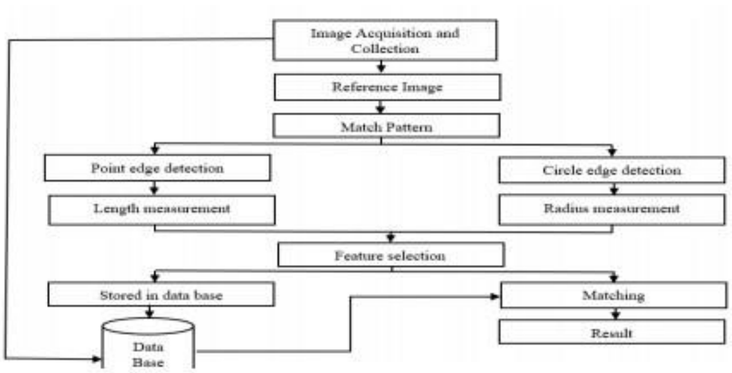


Fig. 1. Machine Vision Process

Fig. 1 show the machine vision process. In the domain of industrial inspection, deep learning models have long been employed to classify product quality. Among these, MobileNets, particularly MobileNetV1, have garnered significant attention due to their streamlined architecture utilizing depthwise separable convolutions. This design choice results in lightweight deep neural networks, making them suitable for resource-constrained environments. Notably, MobileNetV1 has demonstrated robust performance, outperforming other popular models in tasks such as ImageNet classification [2]. Building upon the success of MobileNetV1, MobileNetV2 was introduced with further enhancements in accuracy and parameter efficiency. Compared to its predecessor and other models, MobileNetV2 offers improved performance while demanding fewer computational resources [3].On the ImageNet dataset ResNet model evaluates residual nets with a depth of up to 152 layers—8× deeper than visual geometry group (VGG) nets but still having lower complexity. An ensemble of these residual nets achieves 3.57% error on the ImageNet test set. As a result, ResNet model won the 1st place on the ILSVRC 2015 classification task [4]. ESPNetv2 network uses group point-wise and depthwise dilated separable convolutions to learn representations from a large effective receptive field with fewer FLOPs and parameters. In image classification, even though ESPNetv2 didn't use any channel shuffle which was found to be very effective in ShuffleNetv1 and delivered better performance than ShuffleNetv1. Compared to other efficient networks at a computational budget of about 300 million floating-point operations per second (FLOPs), ESPNetv2 delivered better performance [5]. Unlike previous models, which were inefficient since they needed high computational resources and cannot be deployed on edge devices, EdgeNeXt model overcame this by introducing split depth-wise transpose attention (STDA) encoder that splits input tensors into multiple channel groups and utilizes depth-wise convolution along with self-attention across channel dimensions to implicitly increase the receptive field and encode multi-scale features [6].

B. Image Processing

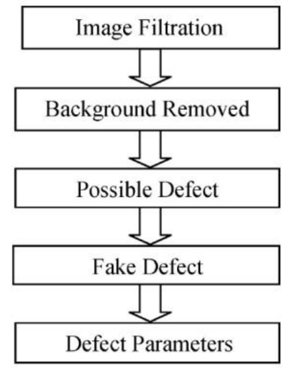
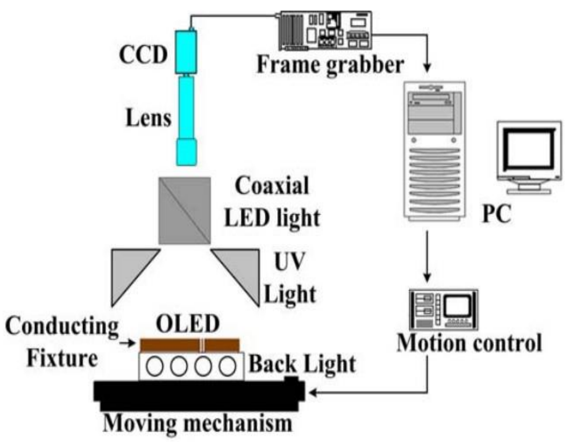


Fig. 2. Image Processing Flow

Fig. 2 show the image processing flow. Image processing is the core technology in a Machine vision based inspection system. The current image processing algorithms are very ripe, and their application range is wider and wider. In particular, numerous brand-new processing techniques, including wavelet and neural network [8], are presented alongside the development of corresponding techniques. Image preprocessing helps the machine comprehend the image better and prepares it for the next phase of image analysis [9]. The rule of picture preprocessing is to take out unimportant data and recuperate valuable genuine data [10]. Picture quality has huge contrasts, because of the picture impacted by various level of openness, genuine nature, pixel, fluffy, form, and different elements. Consequently, based on image quality, the appropriate preprocessing method must be chosen [11].

Methods in the frequency domain and the spatial domain are typically used in image preprocessing. The fundamental preprocessing calculations incorporate grayscale change, histogram balance, different sifting calculations in light of spatial and recurrence areas, and so forth. Furthermore, numerical morphology can likewise be utilized for picture denoising [10]. Classification, localization, and segmentation are three representative machine vision-based defect detection tasks in industrial production. The subsequent image analysis may be aided by some basic image preprocessing techniques, which may also occasionally address a few straightforward tasks related to defect detection. More image processing techniques are required to extract sufficient features for comprehending defect information in the majority of defect detection scenarios. Convolutional neural networks (CNNs), deep belief networks with time-sequenced characteristics. DBNs and SAEs can help multi-feature fusion detection achieve better effect and accuracy [10].

C. OLED Film Inspection



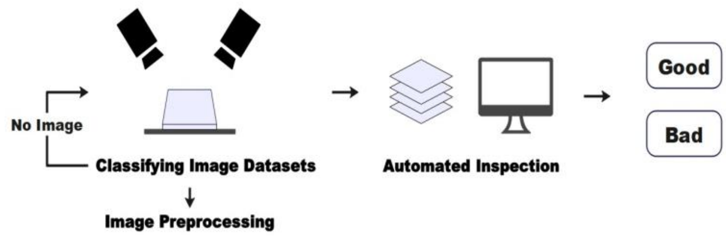
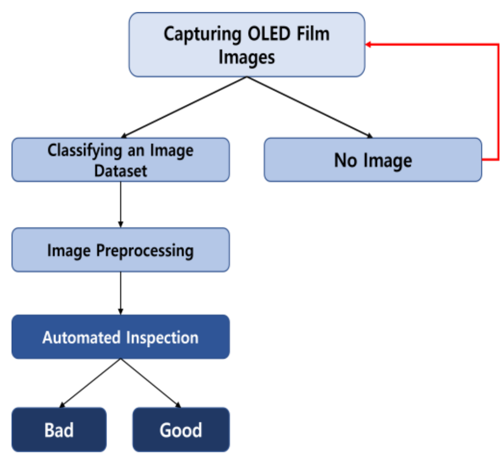


Fig. 4. Overall System Framework



(DBNs), and stacked auto-encoders (SAEs) are the primary types of deep learning network architecture used for image feature learning.

Despite utilizing top-tier materials and sophisticated encapsulation structures, organic compounds within OLEDs remain highly vulnerable to moisture and oxygen exposure. This susceptibility often leads to irreversible damage, manifesting as dark spots where light emission is significantly compromised [12].

Presently, automated optical inspection (AOI) stands as a common practice in production for detecting pre-defined Mura, offering precise and rapid results compared to human inspection. However, AOI faces a limitation in its inability to identify new Mura. Upon recognizing this challenge in OLED defect detection, researchers turned to deep learning algorithms. As depicted in Fig. 3, OLED Film application in AOI systems exemplifies this approach. Test results underscored exceptional performance, not only in identifying previously learned defects but also in detecting multiple defects [13].

In contemporary times, machine vision-based optical detection technology has emerged as a focal point within the electronics equipment sector. Techniques such as image segmentation and band-pass filtering have found extensive application in detecting surface defects, including those present in printed circuit boards and thin-film transistor liquid crystal displays (TFT-LCD). Notably, OLED screens often exhibit various defects, encompassing blemishes and Mura defects, juxtaposed against periodic texture backgrounds. Analyzing these defects in the frequency domain reveals their correspondence to high-frequency components. Frequency components and periodic texture backgrounds typically align with low-frequency components. Employing a high-frequency filter enables the extraction of defect information by effectively filtering out the periodic texture background, leaving behind only the pertinent defects [14].

III. OLED Film Inspection System

A. System Architecture

Fig. 4 shows the system framework of the OLED Film Inspection Architecture in detail and Fig. 5 is a diagrammatic visual representation of the system architecture in Fig. 4, which provides a more concise representation of the various

phases and configurations and serves as an aid to understanding the system framework. This framework shows OLED film image processing step by step, and utilizes machine vision and machine learning technology to perform defect detection and quality control. First, an image of the OLED film is taken using a Multi-Optical System. This is an important step to analyze the surface of the OLED film in detail and capture its characteristics. The Multi-

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Optical System is a key technology that enables the visual inspection of OLED films and is responsible for acquiring accurate images under various lighting conditions. Second, we move on to curating the image dataset. In this process, we categorize the images into various categories. There are seven categories in total, and classification is important to utilize the dataset for the automated inspection process. Third, the image data is preprocessed. Preprocessing is essential for recognizing various features and patterns. This allows us to more accurately extract the data needed to identify and classify defects in OLED films. Fourth, Classification and

Segmentation is used to categorize the data and determine the results of good and bad products. The model accurately classifies OLED films into good and bad based on what it has learned and outputs the results. Through this process, the OLED film inspection system effectively utilizes machine vision and machine learning technologies to identify and classify defects. This greatly improves quality control and production efficiency. It is an important architecture that leads to innovative development in the field of OLED film production and quality control.

Fig. 6 is a diagram detailing the image processing process of OLED Film Inspection Architecture. The process proceeds

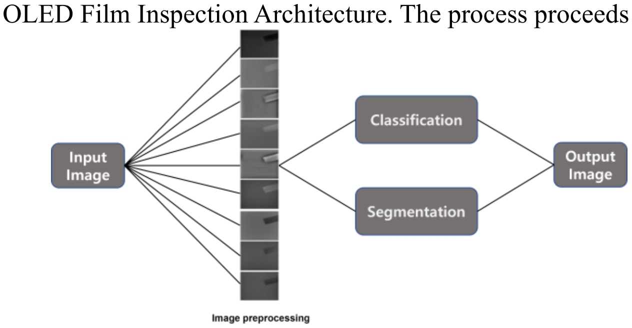

Fig. 6. Inspection Sequence

as follows when OLED film image data is entered into the system. First, the image data is classified into seven categories in the image data classification. The classified data plays an important role in organizing the image dataset to be used in the Classification and Segmentation steps. Classification is an essential step to deal with various bad items, and it organizes the data by considering the characteristics of each item. This is followed by classification and segmentation. Classification separates the good from the bad, determining whether each image is good or bad. Finally, the quality inspection stage checks the quality of the product based on the results obtained during classification and segmentation. Defective items are accurately identified and marked, and good products are passed. In this process, machine vision and machine learning technologies are utilized to accurately inspect the quality of the product and detect defective items. Through this image processing process, the OLED film inspection system accurately identifies and classifies various defective items and performs quality inspection efficiently.

B. Multi-Optical Image Processing

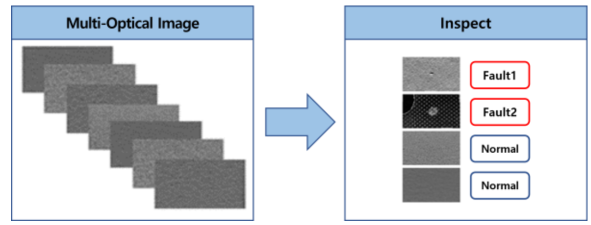

Fig. 7. Multi-Optical Images

Fig. 7 is image data taken from various angles of OLED film using the Multi-Optical System. Shooting from various angles is one of the important factors to more accurately evaluate the quality of OLED film and detect various defects. A total of seven different angles are attempted, and the seven Image data obtained from each angle are variously named REF, INH, INV, IN2, RGH, RGV, and RG2. These various image data are utilized to detect various defects by utilizing each feature. These different angles and image data allow machine vision to detect various types of defects such as scratches, stains, bubbles, and pressing, and play a key role in quality control, especially for extremely sensitive products such as OLED films. Utilizing a variety of image data helps to analyze the surface condition of the product in detail and identify the type of defect. Therefore, defect detection using various angles and image data is one of the most important technologies in this architecture and plays a major role in accurate quality control and increasing the efficiency of the production process. By utilizing this variety of information, manufacturers can reduce the defect rate in the production process and deliver the highest quality products.

IV. Implementation and Results

In this paper, data sets acquired in the actual field are used and designed for automatic inspection of OLED Films. The data set acquired in the actual field consists of 1,000 images, synthesized into one image after taking the image seven times. The experiment was conducted with 210 datasets and 30 images by category of defects.

TABLE I
DEVELOPMENT ENVIRONMENT

	OS	CUDA	cuDNN	Matrox MIL	Numpy	Python	GPU
Development Environment	Window 10 Home	v11.8	v8.24	v10.0	v1.26.0	v3.9.18	NVIDIA GeForce RTX 3090 Laptop GPU

As can be seen in Table I, the development environment of this study is as follows. OS: Windows 10 Home; CUDA: v11.8; cuDNN: v8.2.4; Matrox MIL: v10.0; Numpy: v1.26.0; Python: v3.9.13; GPU: NVIDIA GeForce RTX 3090 Laptop GPU.

A. Data Processing

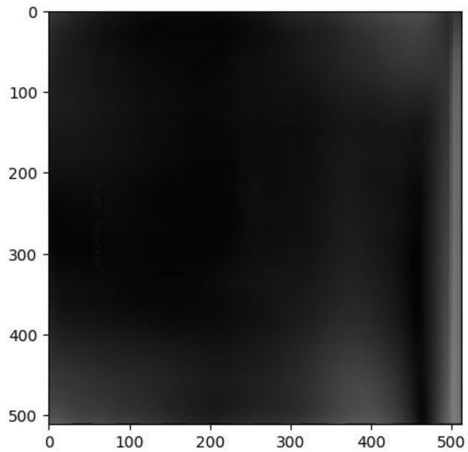

Fig. 8. Image Data Sample (IN2)

Fig. 8 explain the image data taken by the Multi-Optical System provides important information for quality inspection of OLED film. This image data consists of various items such as IN2, INH, INV, REF, RG2, RGH, and RGV, which can be used to detect various defects such as stamped, scratched, and stained OLED films. Machine Learning technology was utilized for image inspection, and 1000 image data was used for training. For each type of defect, the experiment was conducted with 30 images divided into good and bad in a 2:1 ratio. This proved that the combination of machine vision and machine learning can be used to effectively detect and classify various defects in OLED films. These results suggest the possibility of introducing innovative technologies in the field of OLED film production and quality control.

TABLE II
DEFECT CLASSIFICATION AND SEGMENTATION FOR OLED FILMS

Defect / Image	IN2	INH	INV	REF	RG2	RGH	RGV
Scratch					O		O
Stain					O	O	O
Circular Bubbles		O					
Circular Object	O	O	O				
Circular Press		O	O				
Line Press	O		O				
Stamped	O	O					

Table II explain details the defect categories and detectable items for each image. This table provides a detailed view of which defect types each image is utilized to detect. It Consider the features of each image to detect and classify different defects.

- INH and INV: These images can measure data in the horizontal and vertical directions of tilt and are used to detect defects such as stamped, line press, etc.
- IN2: IN2 images can measure absolute value data in the horizontal and vertical directions and are utilized to detect defects such as Circular Object, Line press, and Stamped. • RGH and RGV: These images can measure surface roughness in both horizontal and vertical directions and are used to detect defects such as Scratch and Stain.

Also not mentioned in the table are the INH Processd and INV Processd entries. These items represent preprocessed data from the original INH and INV image data, and are intended to detect weak gradient defects. We did not use them in this experiment. In this experiment, we utilized six of these seven items to test different types of defects and experiment with defect detection. Through this, we verified the ability to effectively detect various defects in OLED films by applying machine vision and machine learning technologies.

B. Results

Fig. 9 shows a good quality image and a bad quality image obtained through multi-optical image processing and classification. The top image shows the good quality image and the bottom image shows the bad quality image. The images were obtained by utilizing various images of IN2, INH, INV and a total of 150 classification tasks were performed. In this important experiment, the classification task performed remarkably well, with an accuracy rate of 95%. This strongly demonstrates the effectiveness of image classification using machine vision techniques in accurately identifying defective items. The high-quality images obtained through multi-optical image processing and classification are expected to revolutionize the field of OLED Film inspection and quality control, helping to improve product quality and increase production efficiency. This research is a clear example of how advances in machine vision technology are revolutionizing modern industries, emphasizing the importance of creating better outcomes in quality control and inspection.

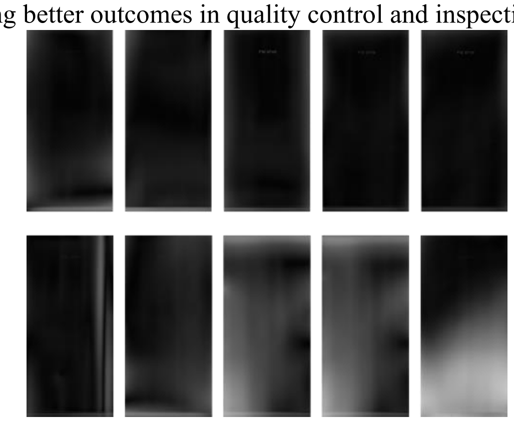

Fig. 9. Classification Images

Fig. 10 is a visual representation of defect detection images generated using multi-optical image processing and segmentation methods. These images were obtained using different optical images RG2, RGH, RGV and the segmentation task was performed on a total of 60 images. Each image has a color representation of the segmentation result. The results of this study showed that the segmentation task performed very well, achieving an accuracy of 80%, which is strong evidence of how effective machine vision and segmentation techniques are in accurately segmenting and identifying defective parts. The ability to effectively segment and accurately detect defective parts is critical to manufacturing and quality improvement, but additional datasets and training are needed to improve these results, and further research and development is expected. This is an important study that highlights the importance of machine vision technology, and we can expect future innovations in defect detection and classification. In the study it expected to play an important role in quality improvement and automated inspection in a variety of industries.

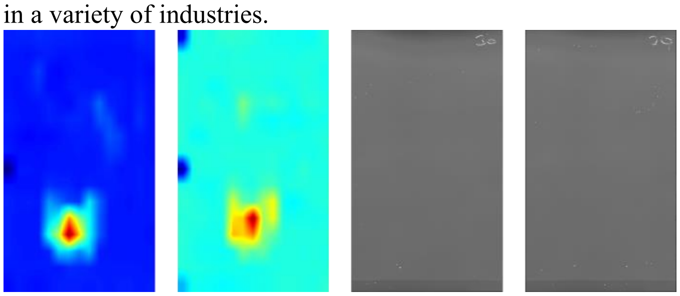

Fig. 10. Segmentation Images

V. Conclusion

This research has played a major role in emphasizing the importance of machine vision technology in the rapidly advancing technologies and industries of the modern world and demonstrating the distinct need for such technology in the field of OLED Film production and quality control. The advancement of the technology and its applications have shown that machine vision has great potential for developing automatic inspection systems and automating manufacturing processes, especially in the OLED Film industry. In this paper, we propose an innovative architecture that applies a multioptical system to acquire images of OLED films, which can detect and effectively classify various defective items.

Experimental results show that the proposed architecture achieves excellent performance in classification using machine learning, which can accurately identify various defective items that may occur during OLED film production. These results emphasize the potential of adopting machine vision technology in OLED film production and quality control to significantly improve quality control and production efficiency. In addition, this research will propose a new architecture for automated inspection in the entire OLED film inspection process by introducing segmentation technology instead of just classification. This will help to identify and separate defects more accurately, providing a more detailed understanding of the location and shape of defects. Overall, this research highlights the importance of machine vision technology in modern industry and demonstrates its practical applicability in OLED film production and quality control, making a significant contribution to promoting technological innovation and development in this field. Based on the results of this study, we can look forward to the further utilization and development of machine vision technology in the industrial field.

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