

Real-Time Classification of Optical Devices Using Rotating Linearly Polarized Light in a Sagnac Interferometer

Rapeepan Kaewon^{1*} Jirasak Wongbongkotpaisan²

^{1,2}*Faculty of Engineering and Industrial Technology, Silpakorn University, Nakhon Pathom, Thailand*

*Corresponding author e-mail: kaewon_r@su.ac.th

Received: 16 June 2025; Revised: 8 December 2025; Accepted: 13 January 2026

Published online: 27 April 2026

Abstract

This study looks at how to create perfectly rotating linearly polarized light using phase-shifting methods in a Sagnac interferometer, aiming to categorize optical devices. Theoretical analysis is conducted using Jones calculus, which provides a framework for understanding the propagation and phase shifting of linear light. Experimental results from the Sagnac interferometer show interference fringes that align with predictions from mathematical simulations. The experimental observations are validated through comparisons with Python-based simulations, ensuring the accuracy of the rotating polarized light characteristics. Additionally, Convolutional Neural Network (CNN) techniques are employed to analyze and verify the interference fringes, further confirming the consistency of the results with Jones calculus theory. This work demonstrates the potential for applying these methods in real-time, non-destructive optical measurements for the inspection and classification of materials such as polarizers and Half Wave Plates (HWP), advancing the field of optical device characterization.

Keywords: CNN, Optical, Polarized, Python-based, Sagnac



INTRODUCTION

Interferometry is a versatile and powerful optical technique widely utilized for precise phase measurements and the inspection of optical materials. Its non-destructive nature allows for the evaluation of material properties without compromising the integrity of the sample, making it invaluable across both laboratory and industrial applications [1], [2], [3], [4]. Among the various interferometric systems, the Michelson, Mach-Zehnder, and Sagnac interferometers are the most commonly employed configurations. While Michelson and Mach-Zehnder interferometers require a complex setup of optical components to generate linearly polarized light beams, the Sagnac interferometer offers a more efficient and simplified approach, utilizing fewer components while maintaining the stability of the light produced [5], [6]. This combination of simplicity and inherent light stability makes the Sagnac interferometer an attractive choice for a wide range of applications [7], [8], [9]. One of the key advantages of the Sagnac interferometer is its ability to generate highly stable, rotating linearly polarized light, a critical resource for advanced optical characterization. This type of light offers insights into the propagation and interaction of light with optical materials and components, which is essential for accurately characterizing material properties. To understand and predict the behavior of rotating linearly polarized light, mathematical models such as Jones calculus are frequently employed. Jones calculus provides a powerful framework for analyzing polarized light propagation, enabling precise predictions of light behavior within complex optical systems. Alongside the advancements in optical techniques, the integration of artificial intelligence (AI) and machine learning (ML) has significantly enhanced the analysis and classification of complex data. Traditional manual classification methods are often prone to human error due to the sheer volume and complexity of data. With the aid of machine learning models, particularly Convolutional Neural Networks (CNNs) [10], [11], [12], the process of classifying and analyzing data from optical systems has become more efficient and precise. CNNs, designed to mimic human visual perception, have proven highly effective in image classification tasks, allowing for accurate analysis of optical systems and components.

The primary objective of this study is to generate and characterize perfectly rotating linearly polarized light using a Sagnac interferometer. The experimental setup detailed in this work integrates optical measurements (including intensity and image-based characteristics) and simulation techniques, specifically Python programming, to model the propagation of light within the interferometric system. By comparing the results from these simulations with experimental data obtained from an oscilloscope and CCD camera, the study aims to verify the presence and quality of the rotating polarized light. Additionally, the research explores the application of a CNN model [13], [14] to classify optical components such as polarizers and Half Wave Plates (HWPs), showcasing the integration of machine learning techniques in optical analysis. This approach further enhances the capability to analyze complex optical systems, demonstrating the potential of combining traditional interferometric methods with modern AI-driven data analysis techniques.

METHODS

1. Process of Generating Rotating Linearly Polarized Light

A laser beam source emits a horizontally linearly polarized beam at 0 degrees, which passes through a light filter to reduce its intensity. The polarization axis of the beam is then adjusted using a half-wave plate (HWP) set at 45°. According to Jones vector theory, the electric field of the incident beam entering the polarizing beam splitter (PBS) can be represented by Equation (1).

$$E_A = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad (1)$$

The PBS separates the beam into a horizontally linearly polarized light component and a vertically linearly polarized light component. This can be explained using Jones matrix theory, represented by Equations (2) and (3).

$$T_{PBSt} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \quad (2)$$

$$T_{PBSr} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \quad (3)$$

Here, T_{PBSt} and T_{PBSr} denote the transmission and reflection components of the horizontally and vertically polarized beams, respectively. Thus, the electric field of the transmitted beam E_{aT} passing through the PBS can be calculated using Equation (4).

$$E_{aT} = T_{PBSt} \cdot E_A = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad (4)$$

Similarly, the electric field of the reflected beam E_{aR} passing through the PBS is given by Equation (5).

$$E_{aR} = T_{PBSr} \cdot E_A = \frac{1}{\sqrt{2}} \begin{bmatrix} 0 \\ 1 \end{bmatrix} \quad (5)$$

From Equations (4) and (5), E_{aT} and E_{aR} represent beams parallel and perpendicular to the PBS axis, respectively. These two beams then experience phase retardation differences. The E_{aT} beam is reflected by a mirror (M1) and directed towards a piezoelectric transducer (PZT), which is attached to another mirror (M2) for frequency modulation adjustments. Therefore, the light reflected by M1 and PZT (M2) before exiting the PBS can be described by Equation (6).

$$E_{aT'} = PBS \cdot M_1 \cdot PZT(M_2) \cdot E_{aT} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 0 \end{bmatrix} e^{i[\delta_x + \delta_x(t)]} \quad (6)$$

where δ_x , δ_y and $\delta_x(t)$, $\delta_y(t)$ represent the phase shifts induced by the reflections at M1 and PZT (M2), respectively. Conversely, the electric field of the E_{aR} beam can be calculated using Equation (7).

$$E_{aR'} = PBS \cdot PZT(M_2) \cdot M_1 \cdot E_{aR} = \frac{1}{\sqrt{2}} \begin{bmatrix} 0 \\ 1 \end{bmatrix} e^{i[\delta_y + \delta_y(t)]} \quad (7)$$

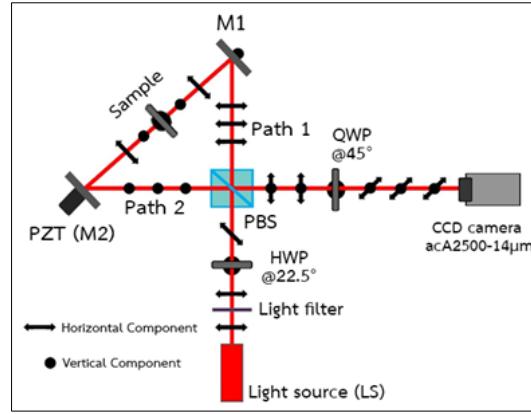


Figure 1: Triangular Sagnac interferometer structure

Both beams recombine at the PBS and are then directed towards a quarter-wave plate (QWP) set at 45°. At this stage, the beams are converted into linearly polarized light. The Jones vector representation of the output electric field can be calculated using Equation (8).

$$E_{out} = Q \cdot E_{aT'} + Q \cdot E_{aR'} \quad (8)$$

where Q represents the Jones matrix of the QWP, given by Equation (9).

$$Q = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & -i \\ -i & 1 \end{bmatrix} \quad (9)$$

By substituting Equations (6) – (9) into Equation (8), the output of electric field under Jones vector theory is obtained as Equation (10).

$$E_{out} = \begin{bmatrix} \sin(\delta_y - \delta_x + \delta_y(t) - \delta_x(t)) \\ \cos(\delta_y - \delta_x + \delta_y(t) - \delta_x(t)) \end{bmatrix} e^{\frac{i}{2}(\delta_y + \delta_x + \delta_y(t) + \delta_x(t) - \frac{\pi}{2})} \quad (10)$$

When the two beams recombine at the interferometer's output, they form perfectly rotating linearly polarized light.

The mathematical results obtained can be used to study the characteristics of rotating linearly polarized light. The output intensity of this light is related to the modulation frequency and the angle (θ) of the polarizer (P). The intensity component of the rotating linearly polarized light can be determined by Equations (11)

$$E_{\theta} = P(\theta) \cdot E_{out} \quad (11)$$

$$E_{\theta} = \begin{bmatrix} \cos^2 \theta & \cos \theta \sin \theta \\ \cos \theta \sin \theta & \sin^2 \theta \end{bmatrix} \cdot \frac{1}{2} (\sin \theta + \cos \theta) \begin{bmatrix} e^{i\theta} \\ ie^{-i\theta} \end{bmatrix} e^{\frac{i}{2}(\delta_y + \delta_x + \delta_y(t) + \delta_x(t) - \frac{\pi}{2})}$$

$$I_{polarizer}^{\theta} = E_{\theta} \cdot E_{\theta}^* = \frac{1}{4} (1 + \sin 2\theta)^2 \quad (12)$$

where E_{θ} and $P(\theta)$ represent the Jones vector output of the light and the angle of the polarizer, respectively. Equation (12) $I_{polarizer}^{\theta}$ expresses the intensity of the rotating linearly polarized light as a function of $0 - 2n\pi$ (in radians) and the modulation frequency.

2. Classification of Optical Devices Using the Sagnac Interferometer Structure

Next, optical device samples are placed into the Sagnac interferometer experimental setup. The samples include a polarizer and a half-wave plate (HWP), with their output light intensities calculated and presented in Table 1.

Table 1: Output light intensity based on optical device type

Optical Device	Output Light Intensity
Polarizer	$I_{polarizer}^{\theta} = \frac{1}{4}(1 + \sin 2\theta)^2$
HWP	$I_{HWP}^{\theta} = \sin^2 2\theta$

where θ represents the angle of the optical device sample, and E denotes the amplitude of the incident light.

3. Generation of Perfectly Rotating Linearly Polarized Light

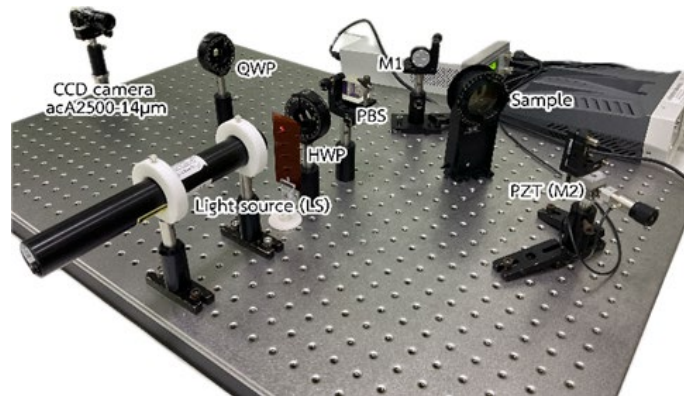


Figure 2: Experimental setup for generating perfectly rotating linearly polarized light using a triangular Sagnac interferometer

As shown in Figure 2, the experimental setup consists of a laser light source that emits horizontally linearly polarized light with a wavelength of 632.8 nm. This horizontally polarized light at 0 degrees passes through a light filter to reduce its intensity. The beam then passes through a half-wave plate (HWP) set at 22.5 degrees, which tilts the polarization to 45 degrees. When the polarized light is tilted at 45 degrees, it contains both horizontal and vertical polarization components. The beam then enters a polarizing beam splitter (PBS), which separates it into horizontally and vertically polarized beams. The horizontally polarized component passes through the pbs, while the vertically polarized component is reflected. The horizontally polarized light passing through the pbs is directed toward mirror1, where it is reflected and then reaches the PZT (M2), which induces phase modulation, causing the light to rotate. The vertically polarized light reflected by the pbs is directed toward PZT (M2), where it also undergoes phase modulation before being reflected toward mirror 1. After these interactions, both horizontally and vertically polarized beams are reflected back to the pbs, forming rotating orthogonal polarized light. When this light passes through a quarter-wave plate (QWP) set at 45 degrees, it is converted into left-hand and right-hand circularly polarized light. Finally, these circularly polarized components combine to form linearly polarized light.

4. Python Program

Writing a Python program requires defining variables to calculate light propagation equations, plotting graphs to display light intensity, and simulating images derived from the calculations. Therefore, the variables based on Jones matrix theory can be analyzed and written as follows:

Python

```
Linear_Horizontal = np.array([[1, 0]])
HWP = (1/np.sqrt(2))*np.array([[1, 1], [1, -1]])
PBST = np.array([[1+0j, 0], [0, 0j]])
PBSR = np.array([[0j, 0], [0, (1+0j)]])
PZT = np.array([[1, 0], [0, i]]) ;
M2 = np.array([(1+0j), 0], [0, (1+0j)])
QWP = (1/np.sqrt(2))*np.array([(1+0j), 1j], [1j, (1+0j)])
```

5. Python Program Process

Define variables for optical device equations, then compute the equation for perfectly rotating linearly polarized light. Next, plot images for comparison with pictures captured by a CCD camera, acA2500- μm . Finally, plot a graph to examine the intensity of the light.

6. Learning with a Convolutional Neural Network (CNN) Model

A CNN is a type of artificial neural network that simulates human vision by analyzing an image as small regions and combining them to detect patterns. The CNN model is used to determine whether the analyzed light is perfectly rotating linearly polarized light.

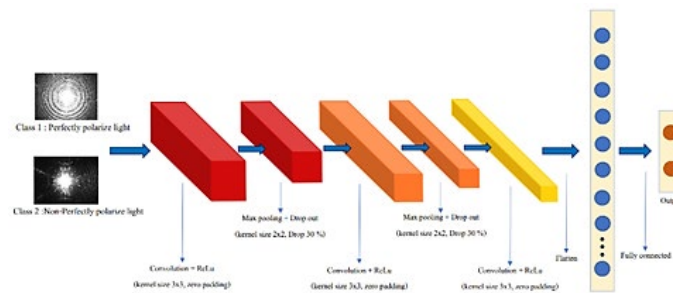
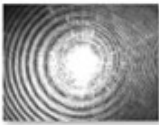
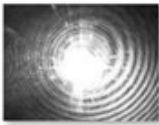
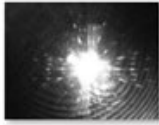
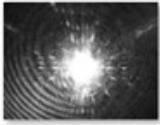


Figure 3: Convolutional neural network model

To utilize a CNN model for verifying perfectly rotating linearly polarized light, multiple interference fringe images must be collected using a CCD camera (acA2500- μm). The CNN is trained to recognize and classify the characteristics of the light. To achieve this, images of both perfectly polarized and imperfectly polarized light are collected, creating two classes: Class 1: Perfectly polarized light, labeled as [1] and Class 2: Imperfectly polarized light, labeled as [0]. The CNN model is trained with 500 images, while 50 images are used for testing, as shown in Table 2.

Table 2: Examples of perfectly polarized and imperfectly polarized light

Perfectly linearly polarize light	None-Perfectly linearly polarize light
 	 
1[1].bmp 2[1].bmp	1[0].bmp 2[0].bmp

7. CNN Model Learning Process

The polarized light from the experimental setup is categorized into two classes: perfectly polarized and imperfectly polarized. The CNN model is trained to distinguish between these two classes. After training is complete, test images of polarized light are inputted into the model to determine whether they belong to the class of perfectly polarized light.

RESULTS AND DISCUSSION

1. Testing Sample Images of Perfectly and Imperfectly Linearly Polarized Light

Images of perfectly rotating linearly polarized light were captured using a CCD camera (acA2500- μm), as shown in Figure 4.

Next, a simulation of perfectly rotating linearly polarized light was conducted using Python. The resulting image exhibits interference fringes similar to those in Figure 4, which were obtained using the CCD camera (acA2500- μm). The two images were compared, and Python was used to plot the intensity graph of light from angles $0 - 2\pi$ radians, as shown in Figure 5, along with the intensity distribution for different axes in Figure 6.

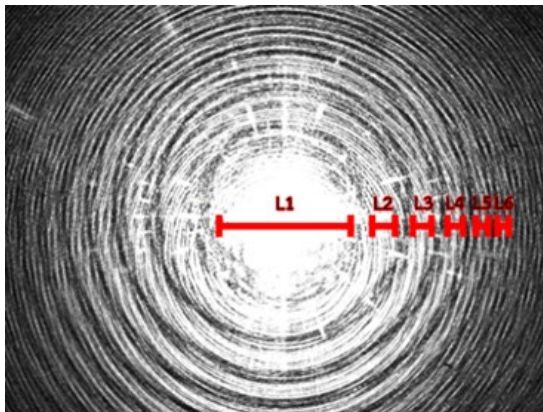


Figure 4: Perfectly rotating linearly polarized light captured by CCD camera acA2500- μm

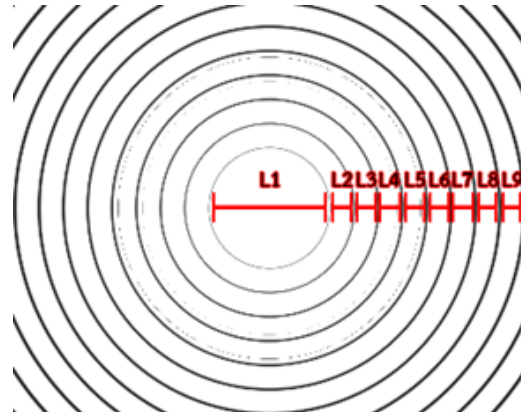


Figure 5: Simulated perfectly rotating linearly polarized light consistent with Jones matrix calculation in Python, Showing Interference fringes from $0 - 2\pi$ radians

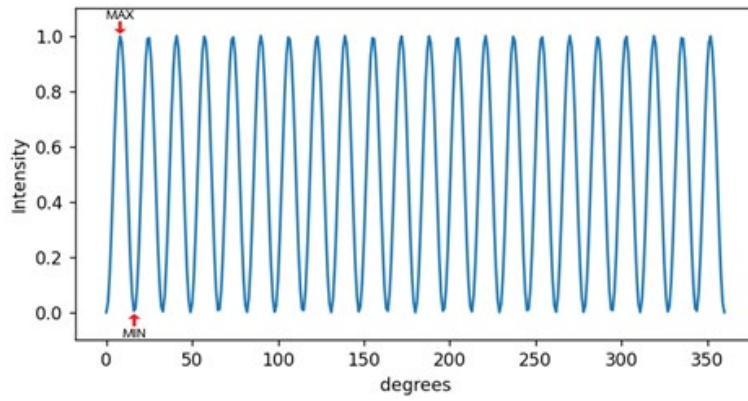


Figure 6: Intensity of perfectly rotating linearly polarized light from $0 - 2\pi$ radians

From Figure 6, the intensity graph of perfectly rotating linearly polarized light shows that intensity varies at different angles. The maximum intensity for perfectly polarized light is 1.0 while the lowest intensity for imperfectly polarized light is 0.0.

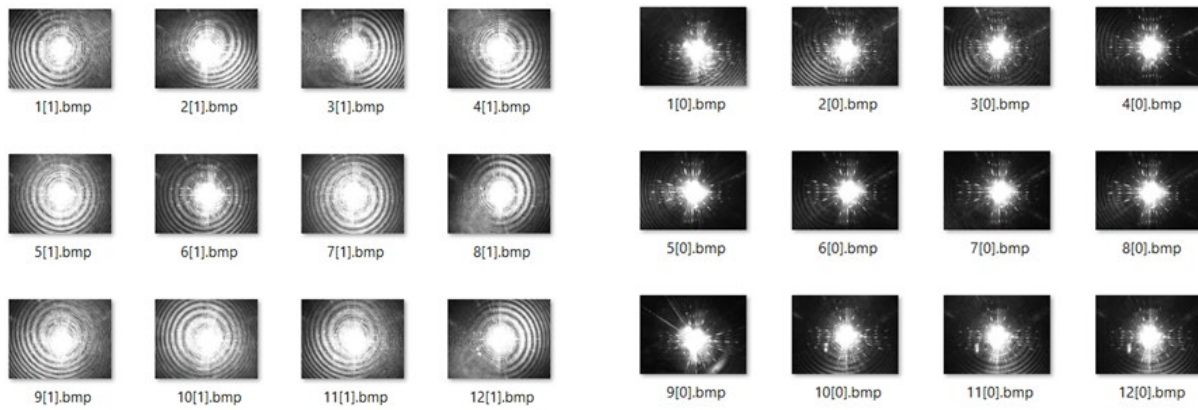


Figure 7: Perfectly rotating linearly polarized light, with the value in [] being 1, indicating a perfectly polarized image

Figure 8: Imperfectly rotating linearly polarized light, with the value in [] being 0, indicating an imperfectly polarized image

In Figure 7, 50 sample images of perfectly rotating linearly polarized light were tested in the Python program. The program successfully classified all images with 100% accuracy. Similarly, in Figure 8, 50 sample images of imperfectly polarized light were tested and the Python program accurately classified them as imperfectly polarized with 100% accuracy.

2. Classification of Perfectly Rotating Linearly Polarized Light with Samples at Angles 0 45 90 and 135 Degrees using a CNN Model

2.1 Classification of Polarizer Samples at 0 Degrees: The CNN model was trained by 500 sample images for 150 epochs. With each epoch, accuracy improved while error decreased. This training allowed the CNN model to classify and recognize test images of different samples. The test was conducted using sample images at 0 degrees, which were previously unseen by the CNN model. The trained model successfully identified these samples as 0 degree polarizers as shown in Figure 9.

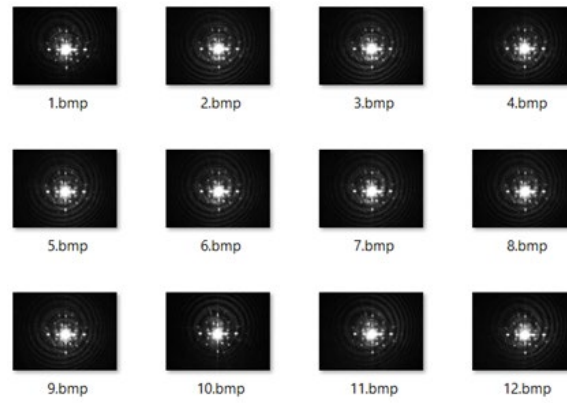


Figure 9: Polarizer at 0 degrees

From Figure 9, 50 sample images of light from a Polarizer at an angle of 0 degrees were tested using a Python program. The program successfully identified them as sample images of a Polarizer at 0 degrees with an accuracy of 100%.

2.2 Classification of Polarizer Samples at 45 Degrees: The CNN model was trained by 500 sample images for 150 epochs. Accuracy increased while error decreased during training. The model was tested on previously unseen sample images at 45 degrees, and it correctly classified them, as shown in Figure 10.

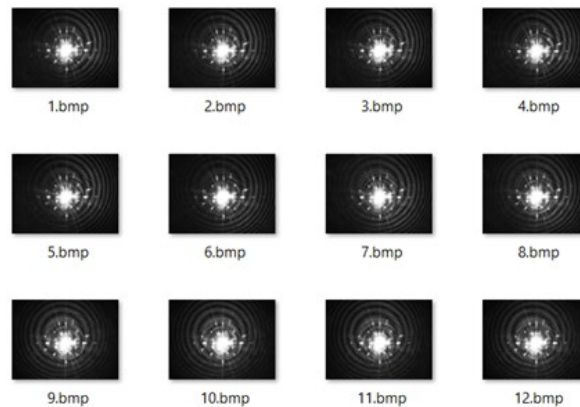


Figure 10: Polarizer at 45 degrees

From Figure 10, 50 sample images of light from a Polarizer at an angle of 45 degrees were tested using a Python program. The program successfully identified them as sample images of a Polarizer at 45 degrees with an accuracy of 100%.

2.3 Classification of Polarizer Samples at 90 Degrees: The CNN model was trained by 500 sample images for 150 epochs. It was then tested on unseen images at 90 degrees. The model successfully identified these images as 90 degree polarizers, as shown in Figure 11.

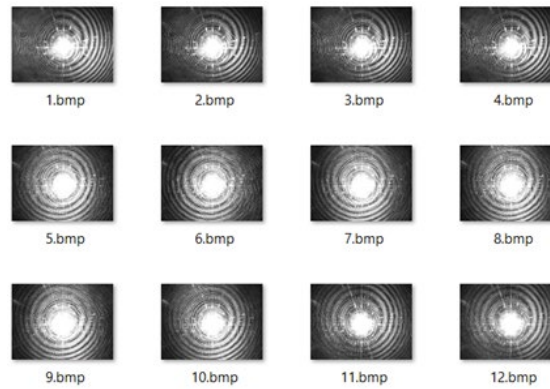


Figure 11: Polarizer at 90 degrees

From Figure 11, 50 sample images of light from a Polarizer at an angle of 90 degrees were tested using a Python program. The program successfully identified them as sample images of a Polarizer at 90 degrees with an accuracy of 100%.

2.4 Classification of Polarizer Samples at 135 Degrees: The CNN model was trained by 500 sample images for 150 epochs. The trained model was tested on previously unseen 135 degree samples and correctly classified them, as shown in Figure 12.

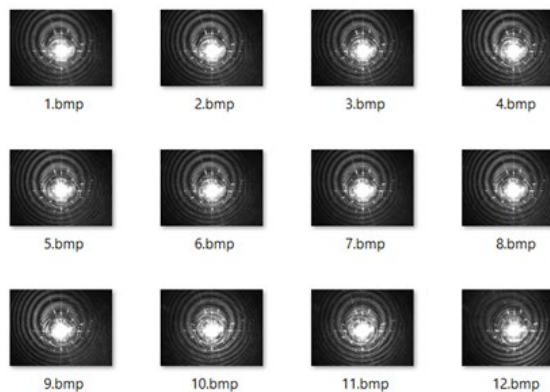


Figure 12: Polarizer at 135 degrees

From Figure 12, 50 sample images of light from a Polarizer at an angle of 135 degrees were tested using a Python program. The program successfully identified them as sample images of a Polarizer at 135 degrees with an accuracy of 100%.

2.5 Classification of Half-Wave Plate (HWP) Samples at 0 Degrees: The CNN model was trained by 500 sample images for 150 epochs and then tested on previously unseen HWP samples at 0 degrees. The trained model successfully classified them, as shown in Figure 13.

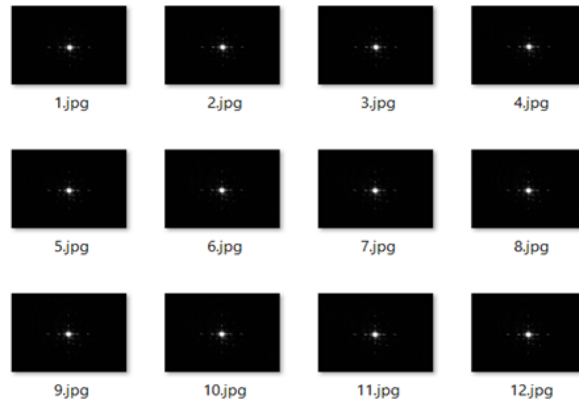


Figure 13: HWP at 0 degrees

From Figure 13, 50 sample images of light from HWP at an angle of 0 degrees were tested using a Python program. The program successfully identified them as sample images of HWP at 0 degrees with an accuracy of 100%.

2.6 Classification of Half-Wave Plate (HWP) Samples at 45 Degrees: The CNN model was trained by 500 sample images for 150 epochs. The trained model was tested on previously unseen 45 degree HWP samples and successfully identified them, as shown in Figure 14.

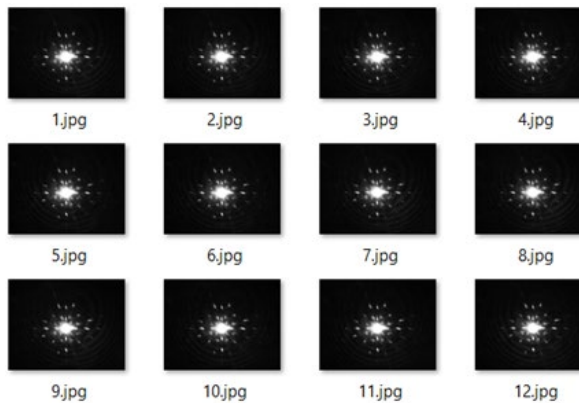


Figure 14: HWP at 45 degrees

From Figure 14, 50 sample images of light from HWP at an angle of 45 degrees were tested using a Python program. The program successfully identified them as sample images of HWP at 45 degrees with an accuracy of 100%.

2.7 Classification of Half-Wave Plate (HWP) Samples at 90 Degrees: The CNN model was trained by 500 sample images for 150 epochs. It was then tested on previously unseen 90 degree HWP samples and correctly classified them, as shown in Figure 15.

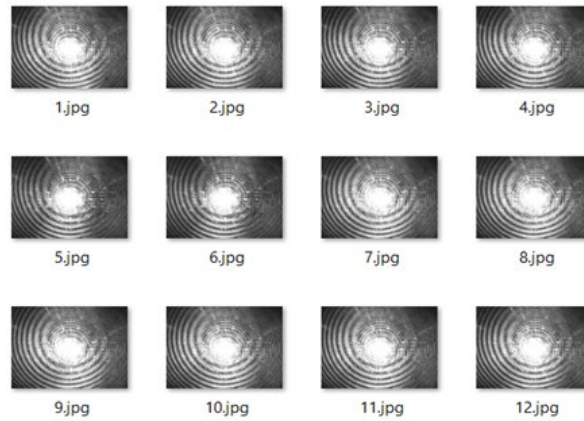


Figure 15: HWP at 90 degrees

From Figure 15, 50 sample images of light from HWP at an angle of 90 degrees were tested using a Python program. The program successfully identified them as sample images of HWP at 90 degrees with an accuracy of 100%.

2.8 Classification of Half-Wave Plate (HWP) Samples at 135 Degrees: The CNN model was trained by 500 sample images for 150 epochs. The trained model was tested on previously unseen 135 degree HWP samples and correctly classified them, as shown in Figure 16.

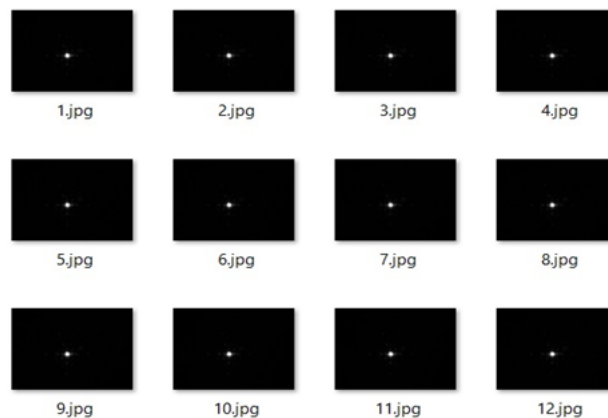


Figure 16: HWP at 135 degrees

From Figure 16, 50 sample images of light from HWP at an angle of 135 degrees were tested using a Python program. The program successfully identified them as sample images of HWP at 135 degrees with an accuracy of 100%. Classification of Samples Polarizer and Half Wave Plate at Angles 0, 45, 90, and 135 Degrees It can be observed that training a CNN model to recognize and classify polarizers at different angles is possible due to the variations in light fringes at each angle. At 0 degrees, light passes through the polarizer the least, resulting in minimal light fringes. At 45 degrees, light can pass through the polarizer by half, leading to an increase in light fringes compared to 0 degrees. At 90 degrees, the maximum amount of light passes through, producing the most prominent light fringes. At 135 degrees, the light fringes are comparable to those at 45 degrees, showing similar characteristics.

CONCLUSION

This research presents the use of a Sagnac interferometer to generate perfectly rotating linearly polarized light with high precision and stability, using fewer components than traditional setups. Jones calculus was employed to simulate light behavior, and experimental results closely matched these simulations. A Python-based model confirmed the accuracy of the theoretical predictions. Additionally, a convolutional neural network was developed to classify polarized light and optical components using CCD camera images. The CNN demonstrated high accuracy and is suitable for real-time quality inspection in industrial applications, improving efficiency and reducing human error.

REFERENCES

- [1] R. Kaewon, A. Bhatranand, Y. Jiraksopakun, E. Siwapornsathain, C. Pawong, and R. Chitaree, "Generation of the rotating linearly polarized light using the triangular cyclic interferometer," in *Proc. 29th Int. Tech. Conf. Circuit/Syst. Comput. Commun. (ITC-CSCC)*, Phuket, Thailand, 2014, pp. 546–549.
- [2] R. Kaewon, C. Pawong, A. Bhatranand, and R. Chitaree, "Fast and effective method to distinguish the polarizing components using a polarizing triangular cyclic interferometer," in *Proc. Asia Commun. Photon. Conf. (ACP)*, Shanghai, China, 2014, pp. 1–3.
- [3] R. Kaewon, C. Pawong, A. Bhatranand, and R. Chitaree, "Polarizing triangular cyclic interferometer for characterizing optical samples with birefringent properties," in *Proc. SPIE – Int. Conf. Photon. Solutions*, Prachuap Khiri Khan, Thailand, 2015, Art. no. 96590L, doi: 10.1117/12.2195890.
- [4] S. Sarkar, N. Ghosh, S. Chakraborty, and K. Bhattacharya, "Self-referenced rectangular path cyclic interferometer with polarization phase shifting," *Appl. Optics*, vol. 51, no. 1, pp. 126–132, 2012.
- [5] C. Pawong, R. Chitaree, and C. Soankwan, "The rotating linearly polarized light from a polarizing Mach–Zehnder interferometer: Production and applications," *Opt. Laser Technol.*, vol. 43, no. 3, pp. 461–468, 2011.
- [6] C. Pawong, R. Chitaree, and C. Soankwan, "Investigation of the use of rotating linearly polarized light for characterizing SiO₂ thin-film on Si substrate," in *Proc. Asia Commun. Photon. Conf. Exhib. (ACP)*, Shanghai, China, 2011, pp. 1–8, doi: 10.1117/12.904420.
- [7] B. Kanseri and H. C. Kandpal, "Mathematical formulation for verification of the Fresnel and Arago interference laws using a Mach–Zehnder interferometer," *Optik*, vol. 121, no. 11, pp. 1019–1026, 2010.
- [8] A. Usman, Y. Jiraksopakun, R. Kaewon, C. Pawong, and A. Bhatranand, "The comparison of multi-stepping algorithms for real-time thickness measurement of transparent thin films using polarization settings," *Laser Phys.*, vol. 32, no. 12, 2022, Art. no. 125401.
- [9] A. Usman, A. Bhatranand, Y. Jiraksopakun, R. Kaewon, and C. Pawong, "Real-time double-layer thin film thickness measurements using modified Sagnac interferometer with polarization phase shifting approach," *Photonics*, vol. 8, no. 12, 2021, Art. no. 529, doi: 10.3390/photonics8120529.
- [10] B. Mahesh, "Machine learning algorithms – A review," *Int. J. Sci. Res.*, vol. 9, no. 1, pp. 381–386, 2020.
- [11] J. D. Kothari, "A case study of image classification based on deep learning using TensorFlow," *Int. J. Innov. Res. Comput. Commun. Eng.*, vol. 6, no. 4, pp. 3888–3892, 2018.
- [12] I. Castiglioni et al., "AI applications to medical images: From machine learning to deep learning," *Physica Medica*, vol. 83, pp. 9–24, 2021.
- [13] A. Serag et al., "Translational AI and deep learning in diagnostic pathology," *Front. Med.*, vol. 6, 2019, doi: 10.3389/fmed.2019.00185.
- [14] R. Kaewon, K. Kittawee, J. Wongbongkotpaisan, and A. Bhatranand, "Validation of perfectly rotating polarized light using Sagnac interferometry: A comparison of Python simulations and machine learning technique," in *Proc. Int. Conf. Photon. Solutions (ICPS)*, Bangkok, Thailand, 2024, Art. no. 135180M, doi: 10.1117/12.3058666.