**MULTIPLEXING OF OAM BEAMS AND DEMULTIPLEXING USING MACHINE LEARNING**

A Dissertation for

Course code and Course Title: ELE-625 PROJECT

Credits: 16

Submitted in partial fulfilment of Master's Degree
M.Sc. in Electronics

by


**Ms. MUSKAN KHAN**

22P0360011


Under the Supervision of

**DR. SANDEEP GAWALI**

School of Physical and Applied Sciences
Electronics

Goa University

Date:

Examined by:

Seal of the School

## DECLARATION BY STUDENT

I hereby declare that the data presented in this Dissertation report entitled, **Multiplexing of OAM Beam and Demultiplexing Using Machine Learning** is based on the results of investigations carried out by me in the MSc Electronics at the School of Physical and Applied Sciences, Goa University under the Supervision of Mr/Ms/Dr/Prof. Sandeep Gawali and the same has not been submitted elsewhere for the award of a degree or diploma by me. Further, I understand that Goa University or its authorities will
be not responsible for the correctness of observations / experimental or other findings given the dissertation.
I hereby authorize the University authorities to upload this dissertation on the dissertation repository or anywhere else as the UGC regulations demand and make it available to anyone as needed.

Khan
Muskan Khan
Signature and Name of Student
Seat no:22P0360011

Date: 20/05/24.

Place: Goa University

## COMPLETION CERTIFICATE

This is to certify that the dissertation report **Multiplexing of OAM Beam and Demultiplexing Using Machine Learning** is a bonafide work carried out by Ms Muskan Khan under my supervision in partial fulfilment of the requirements for the award of the degree of Masters in the Discipline Electronics at the School of Physical and Applied Sciences, Goa
University.

Dr. Sandeep Gawali

Signature and name of supervisor

School of Physical and Applied Sciences Goa University

Date: 20/05/24

Signature of Dean of the School/HoD of Dept

School/Dept

Stamp

Date:

Place: Goa University/Name of college

Contents

# PREFACE

In optical communication, the demand for higher data rates and capacity is ever-growing. Traditional techniques are not enough, so machine learning can enhance them. This topic explores how machine learning can improve multiplexing and demultiplexing techniques in OAM-based systems. We will delve into the fundamentals, complexities, and potential of machine learning techniques such as classification and regression algorithms. This book provides valuable insights into the synergy between machine learning and optical communication, giving a glimpse into the future of high-speed data transmission.

## ACKNOWLEDGEMENT

I would like to express my gratitude to everyone who has helped me in my project.

I express my deep gratitude towards all the teaching faculty Prof. Rajendra. S. Gad, Dr. Jivan. S. Parab, Dr. Marlon Sequeira, Dr. Narayan Vetrekar, Dr. Aniketh Gaonkar and Dr. Sandeep Gawali for their support and guidance throughout the completion of the project. Their knowledge and suggestions have been crucial in helping us plan, carry out, and execute the project. I would also like to thank our non-teaching staff for their support and encouragement.

I would like to express my gratitude to my family and close friends for their unfailing support and inspiration during this project.

# ABBREVIATIONS

| | |
|---|---|
| OAM | Orbital angular momentum |
| SVM | Support vector machine |
| Lg | Laguerre-Gaussian |
| VB | Vortex beam |
| LGB | Laguerre Gaussian beam |
| $\Phi$ | Phi |
| $\pi$ | Pi |
| SAM | Spin angular momentum |
| FSO | Free space optical |
| BER | Bit error rate |
| ML | Machine learning |
| ANN | Artificial neural network |
| CNN | Convolutional neural network |
| D2NN | Diffractive deep neural network |

# ABSTRACT

Our proposed project aims to explore a novel technique for the demultiplexing of orbital angular momentum (OAM) beams in free-space optical communication. Conventionally, OAM beams are multiplexed at a transmitter and then propagated to a receiver where they are demultiplexed based on their orthogonality properties. However, here we propose a new approach that utilises a support vector machine (SVM) as a classifier to demultiplex these beams by capturing the unique multiplexing intensity pattern. This technique offers several benefits, including the elimination of alignment requirements, relaxation of orthogonality constraints, and the avoidance of costly optical hardware. Our findings suggest that the proposed SVM-based technique outperforms the conventional method and can significantly enhance the channel capacity of free-space optical communication. Results show that the SVM-based demultiplexing method is able to demultiplex combinatorically multiplexed OAM modes from a fixed set with >70.00 % accuracy.

# CHAPTER 1

# 1. INTRODUCTION:

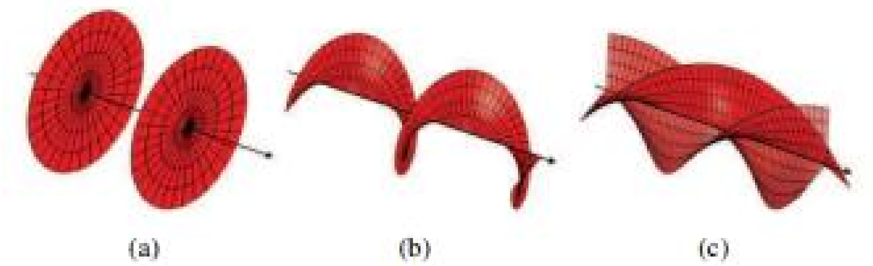
Light is one of the main carriers of information in communication and enhancing its capacity and spectral efficiency is a goal in academia and industry. The Laguerre-Gaussian beam (LGB), with its orbital angular momentum (OAM) component, can be used in communication technology and simultaneously meet the high criteria required for cloud computing, the Internet of Things, 5G communications networks, and other upcoming technologies. Researchers studying OAM mode probability density modulated spatial splitting phenomena, and OAM multiplexing technology in free space have investigated LGB, the first studied vortex beam, in great detail. A new method of modulating information involves carrying various OAM modes while modulating it into LGB. Recently, the orbital angular momentum (OAM) of light has been considered for multiplexing data in free space, optical fibres, and nanoscale.

## 1.1 BACKGROUND

In 1992, Allen et al. introduced the concept of Orbital Angular Momentum (OAM) with that of optical vortex. An optical vortex beam has the ability to carry orbital angular momentum (OAM) wherein the planes of consistent phase of the electric and magnetic vector fields form a corkscrew or helicoid which runs in the direction of propagation. The vortex's topological charge, which denotes the number of twists that the light undergoes in one wavelength, is a defining characteristic of the vortex. The greater the number of twists, the faster the light rotates around the axis. As a result, the OAM carried by the optical vortex can theoretically have an infinite number of eigenstates and is defined in an infinite-dimensional Hilbert vector space. The potential applications of OAM in the field of communications are vast, despite some issues that need to be addressed prior to full deployment. If the OAM dimension of photons can be fully leveraged for information modulation or multiplexing, the information capacity of a single photon can be significantly improved, resulting in a boost in the transmission capacity of single-wavelength and single-mode fibres. Furthermore, because the vortex beam has a helical wavefront, its axial centre field in the direction of propagation is null, presenting opportunities for applications in particle manipulation and imaging.

An optical vortex beam has the ability to carry orbital angular momentum (OAM), as discovered by Allen et al. in 1992. This beam has a special spatial structure that causes the phase front to "twist" in a helical pattern as it propagates and the amplitude to have a ring-like doughnut profile. Beams with various OAM values can be orthogonal to each other. When it comes to OAM multiplexing technology, modulated spatial splitting phenomena, and OAM mode probability density in free space, LGB is the first vortex beam that has been thoroughly examined by researchers. There is a novel method of modulating information that carries several OAM modes and is modulated into LGB.

Laguerre-Gaussian (LG) modes, which have an exp (i $l$ φ) phase term characterising an on-axis phase singularity of strength l, can be used to explain light carrying OAM. LG modes are identified by their waist size (w0) and radial index (p), in addition to the number l. The LG modes used here have p = 0, and their intensity cross-sections show one bright ring with no on-axis intensity f**or l 6 = 0**. The ring's radius scales with l for a given waist size, w0. The highest value of l that can be employed is limited by the finite apertures present in all optical systems. The twist number and direction of the helical wavefront depend on the magnitude and the positive or the negative of *l*. When *l* = 0, OAM beams degenerate to Gaussian beams.




The helical phase fronts of OAM waves: (a) $l = 0$, (b) $l = 1$, and (c) $l = 3$.

The OAM mode order is represented by the number of 2π phase changes in the azimuthal direction. These organised beams are a subset of the Laguerre–Gaussian (LG $lp$) modal basis set in free space, which has two modal indices: (1) p + 1 indicates the number of 2π phase changes in the azimuthal direction, and the size of the ring increases with p. Due to its potential uses in numerous different fields, orbital angular momentum (OAM), which characterises the "phase twist" (helical phase pattern) of light beams, has recently attracted attention. Using OAM for optical communications is particularly promising since

a) coaxially propagated OAM beams with various azimuthal OAM states are mutually orthogonal,
b) inter-beam crosstalk may be reduced,
c) the beams can be multiplexed and demultiplexed effectively.

Multiple OAM states could thereafter be used as various carriers for multiplexing and transmitting various data streams, potentially boosting the system's capacity.

It is commonly known that a light wave can be seen to carry both spin angular momentum (SAM) and OAM when interpreted in a quantum mechanical manner. OAM can be understood to characterise the 'twist' of a helical phase front, in contrast to SAM (e.g., circularly polarised light), which is distinguished by the direction of the electric field. An OAM-carrying beam often features an annular "ring" intensity profile with a phase singularity at the beam centre due to the helical phase structure. Orthogonal-to-coaxial (OAM) beams can be characterised as orthogonal states depending on the discrete "twisting" rate of the helical phase.

More research is being done on vortex beams with orbital angular momentum (OAM). The OAM beams have a phase singularity, a helical wavefront, and zero intensity in the beam's core. OAM beams have a broad range of potential applications in the disciplines of optical communication, rotating body detection, and particle manipulation due to their distinctive phase properties.

Many methods have been put forth and proven effective for producing OAM beams. A laser cavity's output could be used to directly produce one or more OAM beams or by transforming an OAM beam outside of a cavity from a basic Gaussian beam. A spiral phase plate, diffractive phase holograms, metamaterials or a cylindrical device could serve as the converter q-plates fibre gratings lens pairs couplers or q-plates. Detecting an OAM beam can also be done in a variety of ways, for example by employing a converter that a conjugate helical phase is produced, or a plasmonic detector is used. OAM may theoretically transport limitless amounts of information since its OAM modes, which have varying topological loads and are orthogonal to one another in space, have an endless number of eigenstates. In actuality, though, OAM's capacity to transmit data is constrained by the transmission environment and the beam's ability to resist jamming. Multiple OAM states could thereafter be used as various carriers for multiplexing and transmitting various data streams, potentially boosting the system's capacity. The OAM multiplexing technique makes use of this feature to load information and combine multi-channel light into one channel for transmission. Moreover, during transmission, crosstalk happens across modes, making it more challenging to identify the OAM of a vortex beam. Consequently, it is crucial to identify vortex beams at the receiving end.

The OAM in optical communications can be used in two main ways. Either an OAM modulation scheme or an OAM multiplexing technique can be used, just like other physical dimensions like frequency, time, complex amplitude, and polarisation. It is possible to encode different data into different OAMs when utilising the OAM modulation scheme. OAM multiplexing, on the other hand, uses the various OAMs as separate channels to transport and deliver the various types of data. OAM multiplexing thus has the ability to significantly boost communication systems' transmission capacity and efficiency.

The optical communications community's main goal is to achieve better data transfer capacities. This has prompted research into the use of various Lightwave physical characteristics for data encoding and channel addressing, such as wavelength, polarisation, phase, and amplitude. Spatial locations and spatially orthogonal modes have been the subject of extensive research in more recent times. Multiplexing of independent data channels is a common technique used in optical communication systems to increase the transmission capacity. By multiplexing multiple OAM beams, each carrying a separate data channel at the transmitter side, the overall data capacity may be enhanced. Upon coaxially propagating via the fibre or free space, these OAM beams on various channels could be effectively demultiplexed at the receiving end. Importantly, because the various OAM beams are orthogonal, there would be minimal intrinsic channel crosstalk.

It is frequently required to enhance the data link's information capacity because of the complexity of the information that must be communicated and/or the amount of time allotted for transmission. Another choice is to use orbital angular momentum (OAM), which enables the multiplexing and transmission of beams with various mode numbers over the same link. When turbulence is absent, OAM beams display orthogonality. This is advantageous for optical FSO communication since multiplexed beams won't interfere with one another, enabling the recovery of each mode. Channel crosstalk, on the other hand, is the result of information mixing between adjacent modes due to turbulence. The signal decreases and information are lost as a result of this crosstalk.

Because OAM beams in various superposition stages have distinct physical manifestations (such intensity patterns), when OAM beams are utilised for multiplexing or encoding, the OAM pattern identification issue can be transformed into an image classification problem. These issues are commonly articulated in terms of bit error rate (i.e., the error rate of transmitted information bits) and recognition rate (i.e., the percentage of pictures properly identified). Different mode numbers can be multiplexed together or optically combined into a single beam due to the orthogonality property of OAM beams; This multiplexed beam must be demultiplexed to determine which modes are present in the signal after it has propagated and arrived at the receiver. We first describe a widely used demultiplexing technique and then we describe our proposed SVM technique.

The use of Orbital Angular Momentum (OAM) beams has the potential to enhance the capacity of information transmission due to their additional degrees of freedom. However, traditional methods for mode detection and demultiplexing require intricate and costly optical equipment. To overcome these limitations, we propose a novel solution based on Machine Learning techniques for demultiplexing OAM modes at the receiver. Our approach is highly user-friendly and reasonably priced. Specifically, we generated an OAM mode scattered field utilising a random phase mask with a known degree of non-uniformity. We then fed the intensity images of these dispersed fields into a Supervised Vector Machine as input. The model was trained using several Laguerre-Gaussian modes ($LGpl$) carrying OAM with $P$ = 0 and $l$ = 1,2,3,4,5,6,7,8. We evaluated the overall accuracy of the model using various photo sets.

Since the orbital angular momentum (OAM) modes are theoretically orthogonal, OAM multiplexing and encoding techniques can efficiently boost the optical communication systems' channel capacity. Nonetheless, the channel distribution has an impact on the OAM modes' phase distributions. The OAM optical communication system's performance would be lowered by particle and turbulence-induced beam absorptions, scatterings, and phase distortions in air and underwater channels.  ML-based OAM beam demodulation has become a prominent research area in the field of OAM optical communications due to its low cost, high speed, high accuracy, large demodulation range, and ease of processing without the need for redundant optical equipment. In 2014, researchers applied a self-organizing mapping neural network, an unsupervised learning model in ML techniques, to OAM optical communications to perform the demodulation task of OAM beams. Since then, the advancements in ML technology, particularly deep learning, have led to a significant improvement in the demodulation accuracy and precision of OAM beams. Consequently, the demodulation of OAM beams has attained a new level of accuracy and precision. Recently, several researchers have concentrated on identifying OAM modes using machine learning (ML) technology in order to enhance the efficiency of OAM optical communication systems. ML technologies outperform classical picture recognition algorithms in terms of noise tolerance and self-study capabilities. This paper reviews machine learning (ML)-based schemes for detecting OAM modes i.e. support vector machines (SVM). Artificial neural networks (ANN), like BP-ANN, are generally the first machine learning (ML) techniques for identifying OAM modes, despite their low detection accuracy (with an 8.33% error ratio in 143 km of transmissions). In contrast, studies employing support vector machines (SVM) are identifying the beam parameters rather than the intensity distributions of OAM beams. The CNN is mainly designed for image classifications thus it has natural advantages in detecting intensity images of OAM beams. The convolutional and pooling operations can make CNNs not sensitive to small offset and extract features by themselves. The research results show that with OAM intensity as the input images, decoding accuracies of LeNet and Alex Net structures can reach more than 99% in even strong atmospheric turbulence no matter with simulations and in lab environments, which are higher than the ANNs. Some improvements of the CNN structures are also made to increase the accuracy. Some researches focus on image transformation of the input pictures, such as angular spectrum transforming, as an OAM detector, researchers employed a type of all-optical neural network known as D2NN, which can achieve relatively high accuracies without time delay. Overall, as compared to conventional OAM sorting techniques, OAM detectors that use machine learning are able to attain excellent detection accuracy.

## 1.2 AIM AND OBJECTIVES

This paper's main contribution is a novel Supervised Vector Machine (SVM) method for identifying the active OAM modes in a broadcast signal. As an additional example of resolving classification issues, SVM has demonstrated superior performance in classification tasks since 1995. Finding the hyperplane with the "maximum interval" of samples is the fundamental concept of SVM classification. Theoretically, if the original space is finite-dimensional, then the sample must be separable in a high-dimensional feature space; convex optimization technology is typically used to solve this problem. By depending only on an intensity image of the distinct multiplexing patterns at the receiver side, our SVM-based demultiplexing technique avoids the need for expensive optical solutions. In a lab setting, we compare our SVM-based method against a conventional demultiplexing technique, conjugate mode sorting, using different OAM mode sets and simulated air turbulence levels. Combinatorically multiplexed OAM modes from a given set of beams were demonstrated to be demultiplexed using the SVM-based approach.

**BASIC BLOCK DIAGRAM**


One major problem for OAM-based communication systems in the free-space communication system is air turbulence, which can result in wavefront distortion of the transmitted beams. The supervised vector machine (SVM)-based method for detecting vortex beams has progressively gained popularity in recent years due to the quick advancement of machine learning. A multi-layer representation learning method with great accuracy has been presented to identify the OAM modes of multiple vortex beams under varying atmospheric turbulence. Gaussian beams of different modes are multiplexed together at the transmitter and are broadcast over the atmospheric turbulence channel. The vortex beam intensity pictures are gathered at the receiver. To expedite the training process, the received intensity pictures of vortex beams sent across various air turbulences are reduced.

This project outlines a novel optical multiplexing and demultiplexing system that utilises the intensity profile generated by a coherent superposition of OAM-carrying Laguerre-Gaussian (LG) modes and a machine learning detection technique. The proposed system aims at generating an intensity profile for data multiplexing based on the selection of p and ℓ indices of LG beams, while the demultiplexing process is performed using support vector machine (SVM). Unlike existing multiplexing systems that require additional extraction of phase information, the proposed technique offers a comprehensive design of a coherent optical multiplexing system that is independent of phase information and instead relies on the number of spatial modes carrying data symbols increased in a limited optical system. Furthermore, the proposed optical multiplexing model lays the foundation for a stable image detection and classification system based on machine learning that only uses the intensity profile for target modes. Thus, the main contributions of this work are

(1) the development of a comprehensive design of a coherent optical multiplexing system based on the superposition of LG modes carrying OAM.

(2) the introduction of a robust demultiplexing system based on intensity profile recognition using the machine learning SVM method.

## 1.3 HYPOTHESIS

The present study aims to investigate the effectiveness of Support Vector Machines (SVM) in learning discriminative features from input data and classifying Orbital Angular Momentum (OAM) modes with high accuracy. It is hypothesized that SVM-based OAM multiplexing techniques can enhance the capacity and spectral efficiency of optical communication systems by utilizing OAM modes for multiplexing multiple data streams. Furthermore, they are expected to demonstrate robustness to channel variations such as turbulence, noise, and other impairments, due to their ability to learn complex decision boundaries and generalize well to unseen data. Additionally, the study anticipates that SVM-based OAM multiplexing techniques will be applicable in real-world optical communication scenarios, offering practical benefits in terms of performance, simplicity, and compatibility with existing optical network infrastructure. Lastly, the scalability of SVM-based OAM multiplexing methods to large-scale multiplexing scenarios is expected, which would accommodate a significant number of OAM modes and data streams while maintaining high classification accuracy and efficiency. The hypothesis suggests that SVM-based OAM multiplexing techniques can offer accurate classification, robustness to channel conditions, capacity enhancement, real-world applicability, and scalability to large-scale multiplexing scenarios.

## 1.4 SCOPE

The present study aims to investigate the potential of Support Vector Machine (SVM) machine learning techniques for encoding information into Orbital Angular Momentum (OAM) modes. OAM multiplexing has been proposed as a promising solution to increase the capacity of optical communication systems by allowing multiple independent data streams to be transmitted through different OAM modes. To achieve this objective, effective methods for representing input data, including intensity profiles, phase distributions, spatial patterns, or other relevant features associated with OAM modes, will be explored. SVM models will then be developed and optimized to learn the mapping between input features and OAM modes, followed by their performance evaluation in terms of accuracy, classification speed, robustness to noise and channel impairments, and scalability to large-scale multiplexing scenarios. Finally, the integration of SVM-based OAM multiplexing techniques into practical optical communication systems will be investigated, taking into account system compatibility, complexity, and real-world deployment challenges. Overall, the findings of this research will contribute to the development of more efficient and robust optical communication systems. Overall, the scope involves exploring the application of SVM machine learning in OAM multiplexing and assessing its effectiveness, robustness, and potential benefits in enhancing the capacity and performance of optical communication systems

# CHAPTER 2

# 2.LITERATURE REVIEW

- In 2004 Graham Gibson et.al proposed that Orbital Angular Momentum (OAM) can be utilized to encode data onto a laser beam for transmitting information in free-space optical systems. The process involves using spatial light modulators to prepare or measure a laser beam in one of eight distinct OAM states. The researchers have demonstrated that information encoded in this manner is secure against eavesdropping since any attempt to sample the beam away from its axis will be subject to an angular limitation and a lateral offset, both of which lead to an inherent level of uncertainty in the measurement. This research provides an experimental understanding of the role of aperture and misalignment of the beam in OAM measurement and demonstrates the uncertainty relationship for OAM..[1]

- In the year 2021 Denis et.al have conducted a thorough analysis of the commonly employed techniques for generating and detecting orbital angular momentum (OAM) optical beams. The study encompasses the usage of diffractive optics, meta surfaces (MSs), and photonic integrated circuits (PICs). Specifically, diffractive optics can be further classified into spiral phase plates, computer-generated holograms, and diffractive optical elements. Meanwhile, MSs offer compactness and high performance relative to conventional DOEs. PICs-based OAM generators can be further subdivided into two categories: out-of-plane OAM generators and in-plane OAM generators. The latter has garnered significant attention due to its capacity to fully exploit the unique features of OAM beams in guided optics. However, to ensure uniform spatial distributions of the multi-coupled waveguide, most integrated OAM generators require exceedingly critical dimension control technology.[2]

- In 2016 For the first time, a method utilising a phased array was suggested to produce high-order OAM beams in the X-band. Based on the planned system, a mathematical model incorporating contributions from the array error was developed, and the effects of the array error on the effectiveness of the EM vortex imaging and the quality of the radiation field were examined. The simulation findings show that both the intensity and the phase-front distributions can fluctuate as a result of array error, particularly phase error.

- In 2016, Fuquan Zhu et.al suggested that the present study has successfully demonstrated the use of perfect vortex beams for a free-space optical communication link. This was made possible through the utilisation of a spatial light modulator (SLM) loaded with phase holograms based on Bessel functions, which enabled the generation of perfect vortex beams at the focal point of a Fourier lens (FL). To ensure the proper transmission of perfect vortex beams in free space, a simple lens and a microscope objective were employed. Moreover, the performance of a communication link using perfect vortex beams carrying OFDM 16-QAM signals was also demonstrated, following the generation, transmission, and demodulation of such beams. Notably, the size of the perfect vortex beam can be easily controlled, hence rendering it highly versatile for use in the field of free-space optical communication..[3]

- In the 2017 paper, GONG et al. used a circular phased antenna array to generate OAM-carrying beams that possess ring-shaped intensities and helical phase fronts. They also propose and validate a communication system that uses OAM based multiplexing. A circular antenna array is used to generate the superimposed OAM mode by using appropriate excitation settings. The transmission characteristics of OAM modes with respect to different transmission distances are investigated. Experimental results show good transmission characteristics between identical transmitting and receiving OAM modes and isolations between nonidentical transmitting and receiving OAM modes. This result lays the foundation for building multiplexing applications using OAM.[4]

- In 2019 Xiaoming Chen et.al proposed OAM multiplexing in a very echogenic setting. It was demonstrated that OFDM and zero-forcing equalisation in conjunction with OAM multiplexing could not only handle the rich multipath effects but additionally enable high-order modulation transmission

- Taira Giordani et.al have proposed a novel approach to categorise vector vortex beams (VVBs) using machine learning techniques. Their method involves the use of convolutional neural networks (CNNs) and principal component analysis (PCA) coupled with support vector machines (SVMs) for efficient extraction of properties of high-dimensional photonic VVB systems. The authors trained a CNN to identify pre-established state classes of experimental images, which resulted in high prediction accuracy. Their work demonstrates the potential of applying advanced machine learning techniques to overcome the challenges associated with the analysis of high-dimensional photonic systems.[5]

- Y. Wang et al have put forth an innovative approach to achieve complex-amplitude modulation in multiple polarisation channels using an all-dielectric terahertz meta surface. Their proposed technique for OAM multiplexing holography involves controlling the amplitude and phase of circularly polarised waves in both the co-polarization and cross-polarization channels independently. This enables the realisation of various types of OAM multiplexing holography in different channels. Additionally, they incorporated cylindrical and elliptical cylindrical structures into a super-pixel, which allowed simultaneous and independent manipulation of the complex amplitudes in three polarisation channels..[6]

- Y. Zhang et. al suggested utilising multiple machine learning techniques to streamline the OAM spectrum system for object identification missions by employing a reference Gaussian beam. They presented two CNN-based deep learning techniques for object parameter identification, including open angle and direction. In contrast to the earlier OAM spectrum analysis system, it might simplify the hardware implementation process and be useful for real-time object feature detection and remote sensing. In the meantime, the CNN model's computation can be further reduced by the mobile net. The demonstrated method may find additional uses, such as tyre pressure monitoring and propeller and fan blade monitoring. Utilising an external source that has been questioned may also aid in the detection of cloaking objects.

- Xiaoming Chen et.al have presented a comprehensive overview of the promising technique of Orbital Angular Momentum (OAM) multiplexing, which enhances the capacity of optical communication systems by exploiting the spatial degree of freedom of light. The authors have elaborated on how OAM modes, characterized by their azimuthal phase variations, can be utilized for creating multiple parallel data channels within a single optical beam. The paper also sheds light on the challenges encountered while implementing OAM multiplexing in highly reverberant environments, such as indoor environments with multiple scattering surfaces. The authors discuss the solutions to mitigate the effects of reverberation in OAM multiplexing systems, including adaptive signal processing techniques to compensate for channel distortions and spatial filtering methods to separate desired OAM modes from reverberant components. [7]

- Yan et al. investigated the application of orbital angular momentum (OAM) multiplexing in order to enhance the capacity and spectral efficiency of millimetre-wave wireless communication links. The researchers exhibit a millimetre-wave link with a data rate of 32-Gbit/s over a distance of 2.5 metres. This is accomplished by utilising four independent OAM beams on each of two polarizations, resulting in a spectral efficiency of approximately 16 bit/s/Hz. Additionally, the team presents a millimetre-wave OAM mode demultiplexer that is capable of demultiplexing four OAM channels with minimal crosstalk.[8]

- A study proposed by Shibun Lu et al. emphasises how orbital angular momentum (OAM) beams can be used to increase optical communication capacity because of their orthogonality and the comparatively unexplored spatial dimension of light. For the design of mode division multiplexing and mode de/multiplexers in communication systems, the work's findings hold great potential for application. This innovative method advances optical communication technology by using an optical diffraction neural network to develop the OAM de/multiplexer.

- Bruno Paroli et.al proposed paper titled "Hybrid OAM-Amplitude Multiplexing and Demultiplexing of Incoherent Optical States," Paroli et al. report on their experimental study of a new approach for multiplexing and demultiplexing incoherent optical states. This technique involves combining Orbital Angular Momentum (OAM) and amplitude modulation to encode information onto optical signals. The authors successfully demonstrated the transmission of multiple data streams over a single optical channel, achieving significantly higher data-carrying capacity compared to conventional methods. Their findings suggest that the hybrid OAM-amplitude technique has the potential to enhance the performance of optical communication systems.[9]

- Jian Wang et.al has recently introduced the latest development. In recent years, optical vortices have emerged as a promising avenue for enhancing data transmission rates and capacity in optical communication systems. These vortices are characterised by their spiral phase fronts and orbital angular momentum (OAM), and offer unique properties that enable the simultaneous transmission of multiple channels of information through different OAM states. Jian Wang, a renowned researcher in this domain, has explored the latest developments and applications of optical vortices in communication networks. He has introduced the fundamental concepts of optical vortices, including their generation using phase masks, spatial light modulators (SLMs), and other techniques. He has also discussed recent advances and emerging trends in the field of optical vortex-based communication, such as hybrid modulation schemes, multiplexing techniques, and their potential applications in cutting-edge technologies like quantum communication..[10]

- Xiaohui yang proposed a paper that focuses on the synthesis of crosstalk between OAM modes of vortex beams in free space for improving the performance of OAM-based free-space optical communication (FSOC) .It addresses the issue of disturbance induced by atmosphere turbulence (AT) and proposes a method to mitigate the crosstalk among different OAM modes .The proposed method involves propagating an OAM-probe beam (OPB) with the same OAM mode as the OAM-data beam (ODB) to generate conjugate distortion in a photoelectric receiver/detector (PD/PR) .The feasibility of the proposed scheme is verified through an experimental setup, which demonstrates significant improvements in the bit error rate (BER). [11]

- Timothy Doster et.al suggested a demultiplexing method that separates the distinct OAM multiplexed signals using machine learning—as represented by a CNN. according to the patterns of intensity. The methodology has demonstrated its ability to effectively manage varying levels of turbulence, surpassing the conjugate mode sorting method. Additionally, they have produced outcomes for varying extremes of both acquired image quality and size. One feature is that the OAM multiplexed signal can be recorded on the receive side using a modest pixel-count imager, provided that there is a sufficient amount of training data. [12]

- Ri Dong Sun et.al proposed a technique using the SVM's machine-learning theory where the OAM of an LGB is found. A machine learning model was suggested that made use of the beam's beam width, beam wander, and scintillation index as characteristic vectors. The simulations produced satisfactory results. It was investigated how the detection accuracy was affected by the quantity of training samples, the transmission distance, and the OAM categorization. The findings demonstrate that the SVM model, when compared to CNN, more accurately determines the OAM of the vortex beam with fewer samples. The range of OAM and the quality of the vortex beam determine the detection accuracy, which is independent of the OAM value's magnitude.[13]

- Peipei Wang et.al proposed a novel approach for manipulating light beams based on a D2 neural network (D2-NN) architecture. This approach is capable of redistributing the phase and intensity of multiple vector beams (VBs), they demonstrated its effectiveness through the design of an orbital angular momentum (OAM) mode coupler and separator. The experimental results show that the energy utilization rate of the OAM modes modulation is exceptionally high at 99.99%, and the mode purity of the output light field exceeds 97%. When the trained mode coupler and separator are employed in an OAM multiplexed communication link, the bit error rates (BERs) of the two OAM multiplexed channels are almost zero with a signal-to-noise ratio (SNR) of 22 dB. Furthermore, our proposed method exhibits excellent communication performance even in a three-way OAM multiplexed communication scenario. Thus, our results indicate that the D2-NN-based light modulation method is highly accurate and energy-efficient, possesses light field information processing capabilities, can simultaneously process multiple OAM modes, and can improve communication performance when applied to optical OAM communication. [14]

- The author Lei Gong et.al proposed the method, called scattering-matrix-assisted retrieval technique (SMART), can reliably separate encoded OAM states from many scattered light sources. Every OAM channel is demultiplexed using the mode decomposition method, and the optical field of a data-carrying vortex beam with OAM superposition states is recovered using a speckle-correlation scattering matrix. Optical communication via non-line-of-sight connections is possible with the SMART due to its strong resistance against system misalignment.[15]

- Erick Lamilla et.al proposed a novel method for generating a coding system that is independent of phase information using coherent superposition of two Laguerre-Gaussian LG beams with orbital angular momentum. This approach utilises a machine learning algorithm known as SVM-ECOC for image prediction, recognition, and classification. To validate the proposed optical encoding model's robustness, a 4-bit data symbol code is designed, which is associated with the intensity profile according to the (p,l) combination. A channel noise consisting of RIN and AWGN is introduced to the images generated in the encoding stage to emulate a real environment. To identify each data symbol, two different algorithms based on an SVM-ECOC model are utilised. .[16]

- Xiaoji Li et.al presented the results of OAM modal recognition of ocean turbulence based on SVM and the simulation of OAM modal recognition under the ocean turbulence channel. Analysis was done on how strong turbulence affected the OAM modal recognition. The findings indicate that when *z* decreased, the OAM modal recognition accuracy grew with time. The recognition accuracy rapidly declined as the number of OAM modes increased. Based on the experimental results, novel concepts for the demodulation and study of optical underwater communication can be proposed, with great potential for both experimental and research applications.[17]

- Rui Chen et.al provides an in-depth analysis of orbital angular momentum (OAM) waves, which possess unique characteristics that differentiate them from traditional plane waves due to their inherent rotational properties. They examined the various methods utilized for generating OAM waves, which include advanced spatial light modulators, meta surfaces, and holography. Additionally, they examined the detection methodologies used to capture these elusive waves, including spiral phase plates and interference-based techniques. They also introduced the potential of OAM waves to revolutionise a wide range of domains. In particular, OAM waves could have a transformative impact on optical communications by enhancing capacity and robustness. Furthermore, they could facilitate advancements in imaging, microscopy, sensing, and quantum information processing. [18]

- L. Allen et.al has experimentally observed that a Laguerre-Gaussian laser mode possesses a well-defined orbital angular momentum that is proportional to the azimuthal mode index, denoted by "I". In this context, we have presented a method that describes how this orbital angular momentum can be extracted from the mode and converted into a mechanical torque. This process can be achieved through the use of astigmatic optical elements, which can also be used to generate Laguerre-Gaussian modes from the more commonly occurring Hermite-Gaussian modes. It is noteworthy that any light beams that possess field gradients, and are not plane waves, will inherently possess a certain degree of orbital angular momentum. However, an improperly phased transformation between transverse laser amplitude distributions may lead to an ill-defined orbital angular momentum. Therefore, it is crucial to create and entirely transform stable, nondegenerate, propagating Laguerre-Gaussian polynomial modes [19]

- Gregorius C. G et.al described a technique that uses two stationary optical components to sort orbital angular momentum (OAM) states of light efficiently. The helically phased light beam corresponding to OAM states is transformed into a transverse phase gradient beam by means of a Cartesian to log-polar coordinate translation carried out by the optical elements. Each input OAM state is subsequently focused to a distinct lateral location by a later lens. Additionally, they provide an experimental demonstration of the notion by separating eleven OAM states using two spatial light modulators to produce the appropriate optical elements.[20]

- Shikun Zhang et.al. the authors of this work have presented a novel technique for measuring the OAM spectrum that makes use of the Dammann vortex grating and the grey-scale algorithm. Without the need for a power metre, the intensity proportion of various OAM modes can be found using the grayscale technique. The OAM spectra of a maximum of six channel multiplexing beams are acquired in the experiment. The main benefit of this approach is its practical simplicity. The image processing programme can handle all aspects of this technique, including the grey-scale algorithm, which is the most involved portion. Additionally, MATLAB and additional applications can be used to construct the processing programme in its entirety. [21]

- In 2018, Cui Xiaozhou and others in this research group used the random phase screen method to simulate the transmission of superimposed LG beams in the ocean turbulence channel and used the CNN of the classic LeNet-5 architecture to identify 8 types of superimposed LG beams. Research results show that the system can maintain a recognition rate greater than 95% when the transmission distance is less than 80 m in the case of weak turbulence (), and maintain a recognition rate greater than 90% within 60 m in the case of medium and strong turbulence **()**. However, in actual underwater channels, there are not only the effects of turbulence, but also interference factors such as the absorption of water molecules and the scattering of particles in the water.[22]

- In this study,Wenjie Xiong et.al presented a Convolutional Neural Network (CNN) approach for identifying Orbital Angular Momentum (OAM) modes. They employ a Gaussian beam to interfere with Vortex Beam (VB) to obtain interference patterns that contain conjugated OAM mode information. The CNN is trained in a supervised manner using the interference patterns obtained under various turbulence conditions as feature extraction objects. They explored the impact of different Gaussian beam waists, VB orders, input sample sets, and CNN structures on the performance of the CNN and highlighted the significance of appropriately setting these parameters. This investigation adds depth and detail to the research.[23]

- Kuang Zhang proposed a comprehensive overview of the generation of OAM vortex beams in the microwave domain. The theoretical foundation of Laguerre-Gaussian beams is presented, where the well-defined orbital angular momentum possessed by these beams is highlighted. The classical techniques employed to generate such beams, including the use of phase plates, reflectors, diffraction gratings, and antenna arrays for transforming plane waves to vortex waves, are also reviewed. In recent years, meta surface has emerged as a revolutionary technology for manipulating electromagnetic properties and functionalities using subwavelength elements. In this context, meta surfaces have been used to transform plane waves to vortex waves carrying OAM, both in reflection and transmission modes.[24]

- Jianchi ye et.al proposed a paper named OAM modes classification and demultiplexing via Fourier optical neural network. This study showcases real-time Fourier optics convolution right after generating an OAM-coded signal within a simulated atmospheric turbulence environment. The researchers developed a new hybrid optical-electronic convolutional neural network that can accurately distinguish between 16 classes of OAM-coded signals with a demultiplexing accuracy of 68.43%, even under strong atmospheric turbulence conditions. This is a significant achievement that highlights the system's potential in demultiplexing high-bit OAM-coded data strings, which can offer advantages in terms of reduced power consumption, latency, and enhanced throughput.[25]

- Kuo Zhang et.al, have proposed and studied a method for all-optical parallel classification that uses OAM mode-encoded diffractive networks to encode the spatial information of multiple objects as OAM modes of the VB. They analysed the OAM mode normalized intensity distribution using OAM spectra for multitask optical classification. If the existing OAM-encoded D2NN can improve its inference accuracy, it can be used for other deep-learning tasks, such as dynamic image recognition and multilabel classification. To solve more complex tasks, they planned to introduce more OAM modes, which may require the use of a more advanced multimode OAM comb as a light source.[26]

- Tianying Lin proposed a new method for predicting the purity of OAM mode in optical fibres using deep learning has been proposed. The method involves training a specific neural network consisting of three convolutional layers and five fully connected layers with pre-processed far-field intensity patterns to accurately determine OAM purity. The trained CNN has achieved an accuracy of over 99% in predicting OAM mode purity, and the technique is demonstrated to be generalizable and robust. Additionally, the proposed CNN architecture can be adapted to handle other types of OAM fibres. This technique offers a simpler and more efficient way to measure OAM purity compared to traditional methods that require bulk optic devices and precise alignment. [27]

- DA Stankevich has proposed a paper that provides a detailed analysis of a neural network demultiplexing method's effectiveness for waves with orbital angular momentum. The study includes both numerical simulations and experimental tests, and the results show that the proposed method performs better than the traditional correlation method in terms of accuracy and efficiency. One notable feature of the proposed method is that it can achieve high performance even with a relatively simple architecture. Generally, systems that rely on neural networks require many layers and complex processing units to achieve optimal results. However, the neural network architecture developed in this study consists of only a few layers, making it possible to implement the demultiplexing method on a simple signal processor. The authors demonstrate that this approach can significantly reduce the system's cost and complexity while maintaining a high level of performance. [28]

- Patrick L Neary and his colleagues proposed a paper addressing the issue of signal attenuation that affects the classification performance of underwater communications. They developed innovative CNN-based models known as SMART, which capture the physics of the attenuation process. Two of these models were trained using automatic differentiation and the radon cumulative distribution transform. These models were then integrated into the classifier training pipeline, and it was demonstrated that their inclusion significantly enhances classification performance even when the trained model is subjected to environmentally attenuated images. This improved classification accuracy is of great significance for future OAM underwater optical communication applications. [29]

- Sanjaya Lohani et.al demonstrated a paper using Deep Neural Networks (DNNs) to classify numerically generated Laguerre-Gaussian (LG) images that are noisy and contain Orbital Angular Momentum (OAM) values ranging from 1 to 100. Despite the challenging nature of the task, these networks are able to achieve error rates of less than 0.5% after just five epochs. The researchers also discovered that by using states with nonzero radial index to increase the effective alphabet size, they were able to obtain similar results of >99% accuracy. Additionally, the researchers demonstrated the ability of these networks to classify experimentally generated superpositions of OAM images with near-unity accuracy. Overall, the findings suggest that deep

Convolutional Neural Networks (CNNs) can accurately and efficiently classify superpositions of OAM states of light.[30]

- A new approach to classify high-dimensional photonic vector vortex beams (VVBs) using machine learning (ML) techniques has been presented. By implementing various ML algorithms like supervised and unsupervised learning, the method of characterizing structured light is more flexible and broader in its applications. The use of inference strategies based on convolutional neural networks (CNNs) and principal component analysis (PCA) enhanced by support vector machines (SVMs) enables the efficient extraction of properties of VVB systems. This approach opens up new avenues for further experimental validations and can be beneficial for various tasks in modern photonics by introducing similar ML ideas into their characterization protocols.[31]

- In a recent study, researchers have demonstrated how machine learning (ML) techniques can be effectively used as advanced signal processing tools in fibre-optic communication systems. With the growing speed, dynamism, and software-defined nature of optical networks, ML and big data analytics are expected to play a crucial role in addressing complex issues that cannot be tackled through traditional methods. Therefore, researchers in the field of optical communications and networking can benefit from having fundamental knowledge and skills in ML to keep pace with the upcoming trends and challenges.[32]

- Rui Ma et.al proposed a paper where they experimentally and theoretically researched on the properties of OAM-dependent speckles that originate from the vortex beam that passes through a ground glass diffuser. It is discovered that an annulus on the cross-correlation map with a radius dependent on their topological charge difference can be created by imposing a cross correlation between the OAM-dependent speckles.. Moreover, an OAM-dependent speckle basis can be employed as a viable contender for demultiplexing data encoded with OAM. The viability of the OAM-dependent speckle-based demultiplexing is demonstrated by the relatively low error rates of the 24-bit RGB and 8-bit grayscale OAM-encoded data.[33]

# CHAPTER 3

# 3. METHODOLOGY

## 3.1: Detection of OAM beam using LG beam equation

The Laguerre-Gaussian (LG) beam is a widely used type of orbital angular momentum (OAM) beam in optical communication systems. It is a particular solution to the Helmholtz equation in a cylindrical coordinate system, which assumes a paraxial approximation. The field distribution of the LG beam can be expressed mathematically using a specific formula. Optical field of LG beam can be represented by

$$LG_p^{(l)}(r, \varphi, z) = A_0(r, z)\exp(il\varphi),$$

where $A_0(r, z)$ is defined as

$$A_0(r, z) = \sqrt{\frac{2p!}{\pi(p+|l|)!}}\frac{1}{w(z)}\left[\frac{r\sqrt{2}}{w(z)}\right]^{|\ell|} L_p^{(|l|)}\left[\frac{2r^2}{w^2(z)}\right]\exp\left[-\frac{r^2}{w^2(z)}\right]\exp\left[\frac{ikr^2z}{2(z^2+z_R^2)}\right]$$
$$\times\exp\left[-i(2p+|l|+1)\tan^{-1}\left(\frac{z}{z_R}\right)\right],$$

where *z* refers to the distance between the input plane and the receiver plane, *r* is the radial coordinates in a polar coordinate system. $l$ is the OAM mode value and is called topological charge which represents the phase change along the directional angle *p* is the radial indices, $wz=w0\ \sqrt{1+z/zR^2}$ represents the beam radius at a distance *z* away from the beam waist, in which $w0$ is the beam waist and, $zR=\pi wo^2/\lambda$ is the Rayleigh range $k=2\pi/\lambda$ is the wave number, $\lambda$ is the wavelength. $Lpl$ is the associated Laguerre polynomial. For LG beams, *l* and *p* determine its light field distribution. When $\boldsymbol{l} = 0$ and $p = 0$, the above equation becomes the light field expression of the Gaussian beam; When $l \neq 0$ and $p = 0$, the light intensity images of LG beams demonstrate a ring-shaped distribution like a donut, and its halo radius increases with the increase of *l*. The light intensity distributions and phase distributions of the LG beams are shown in below figures with the transformation of *l*, while keeping *p* at 0, the light intensity distributions will vary accordingly.

The below figures show the intensity and phase distribution of different OAM modes where (*l* = +5, +7,+3 ,+8 ,+6 ,-9 ,-4 ,+2 ,-5 ,+4) and the multiplexed image of these l modes.

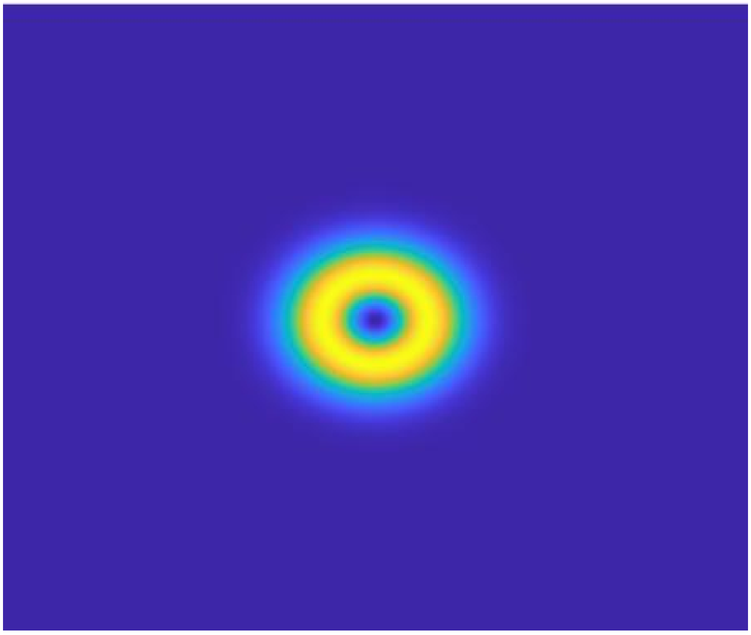


*fig1: intensity profile l=+5*

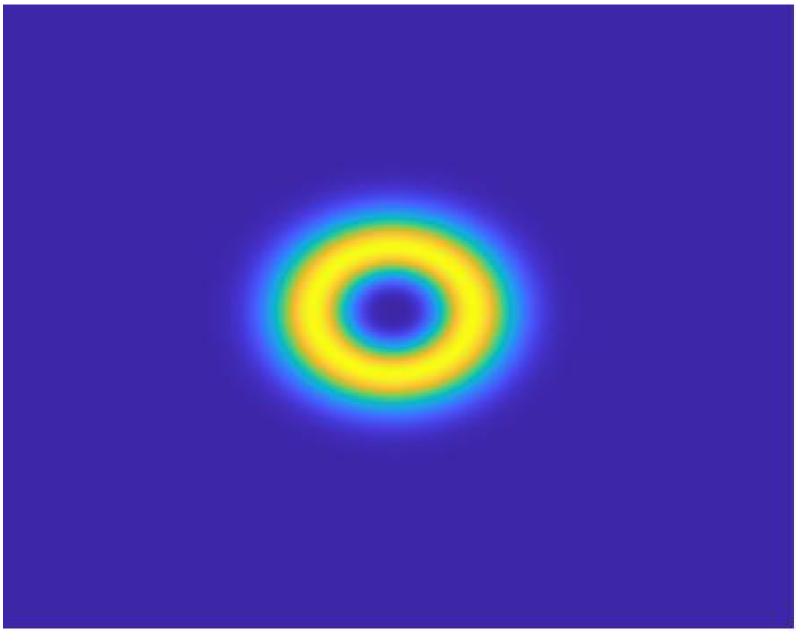


*fig 2:intensity profile l=+7*

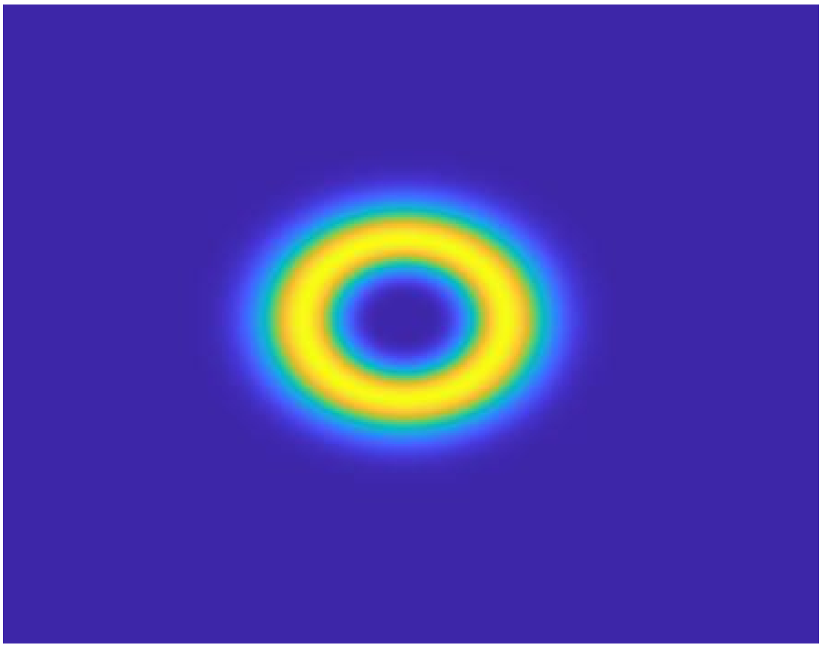


*fig 3:intensity profile l=+3*

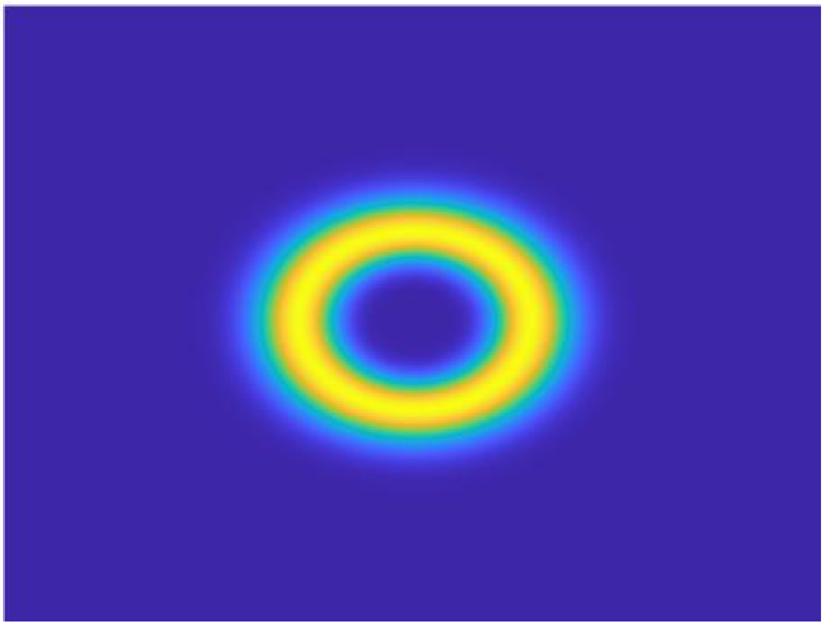


*fig 4:intensity profile l=+8*

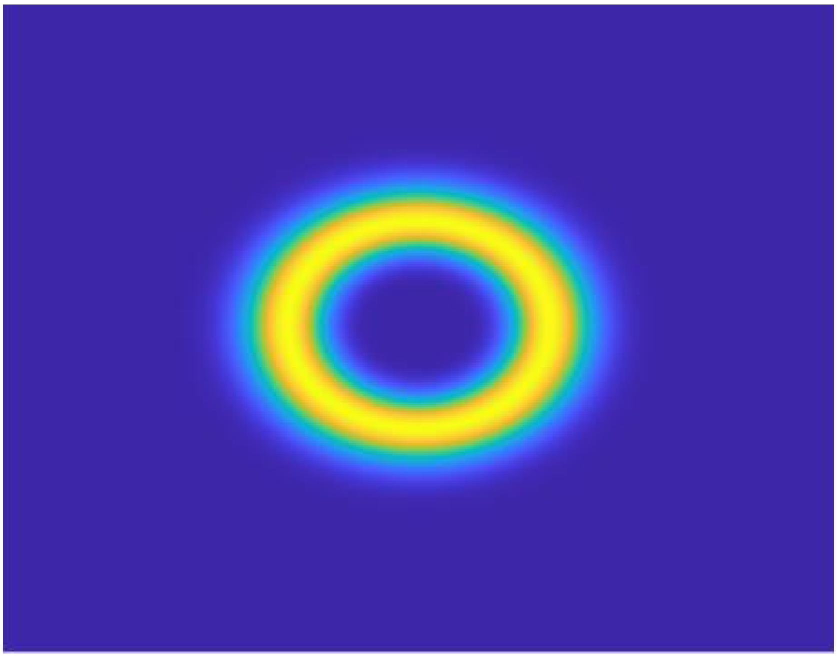


*fig 5:intensity profile l =+6*

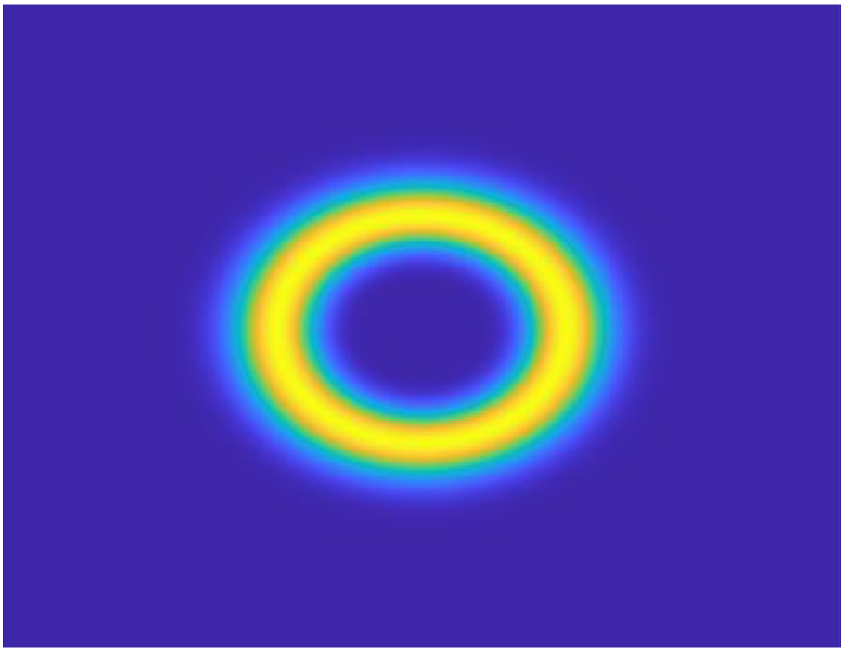


*fig 6:intensity profile l=-9*

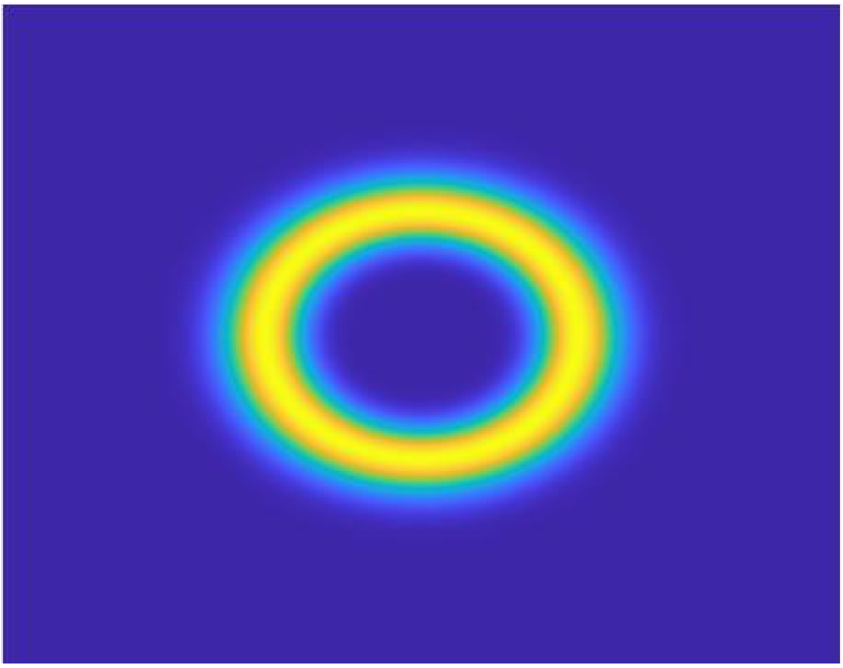


*fig 7:intensity profile l=-4*

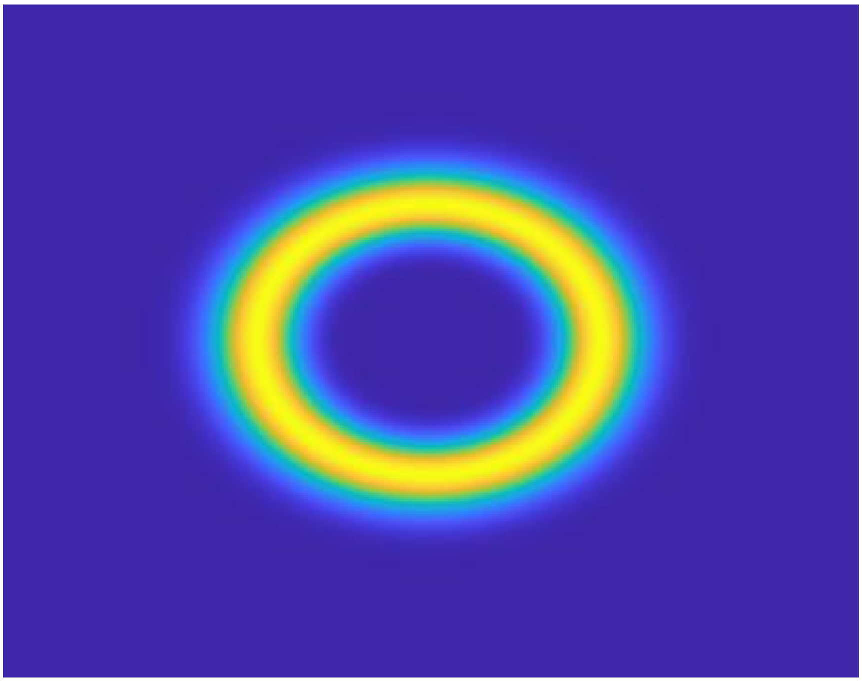


*fig 8:intensity profile l=+2*

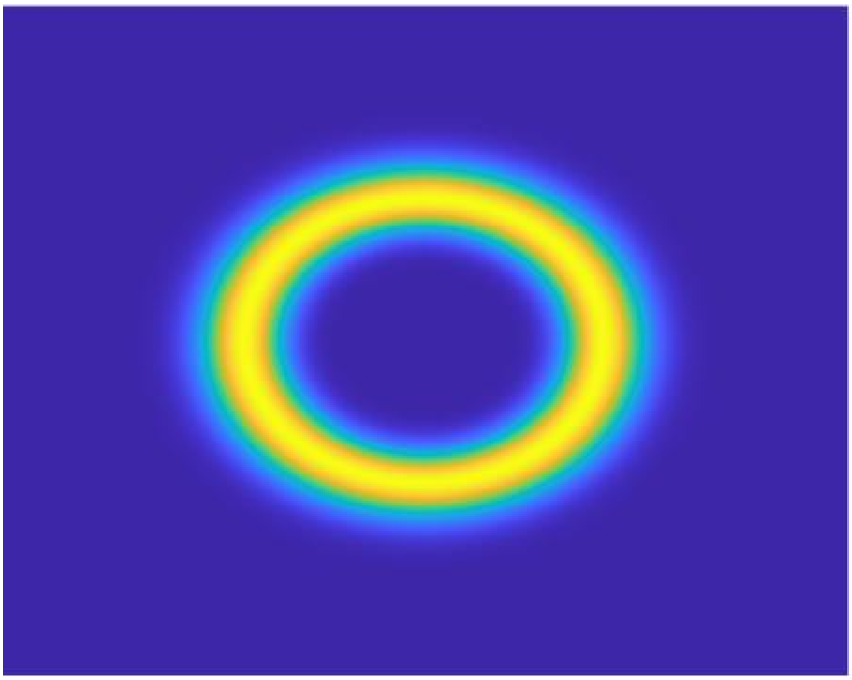


*fig 9:intensity profile l=-5*

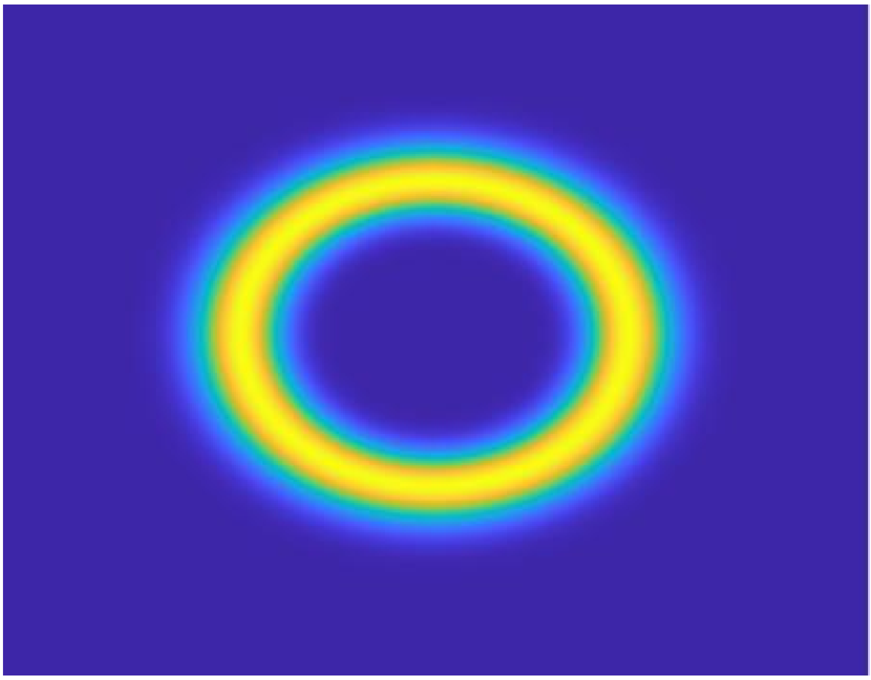


*fig 10:intensity profile l=+4*

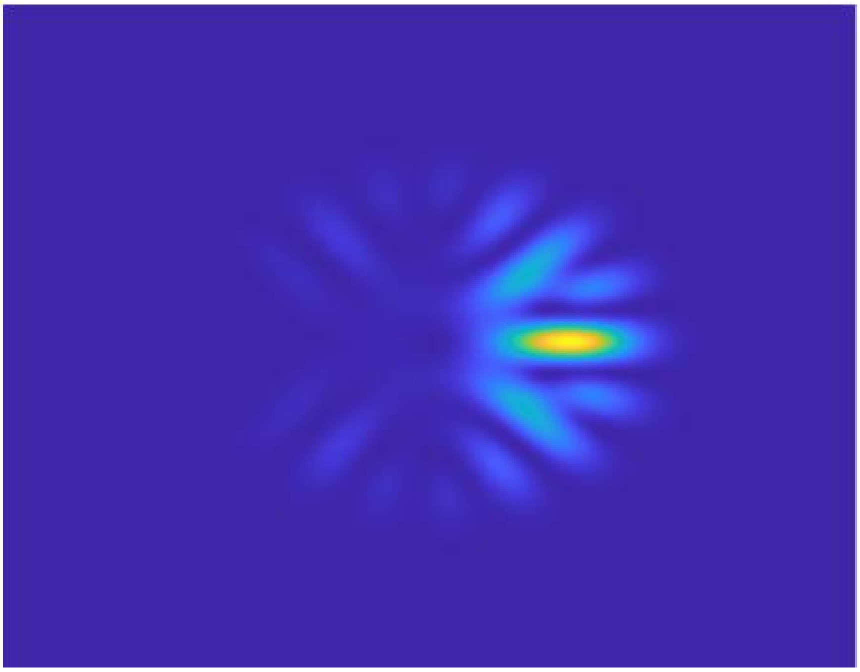


*Fig 11: Multiplexed image*

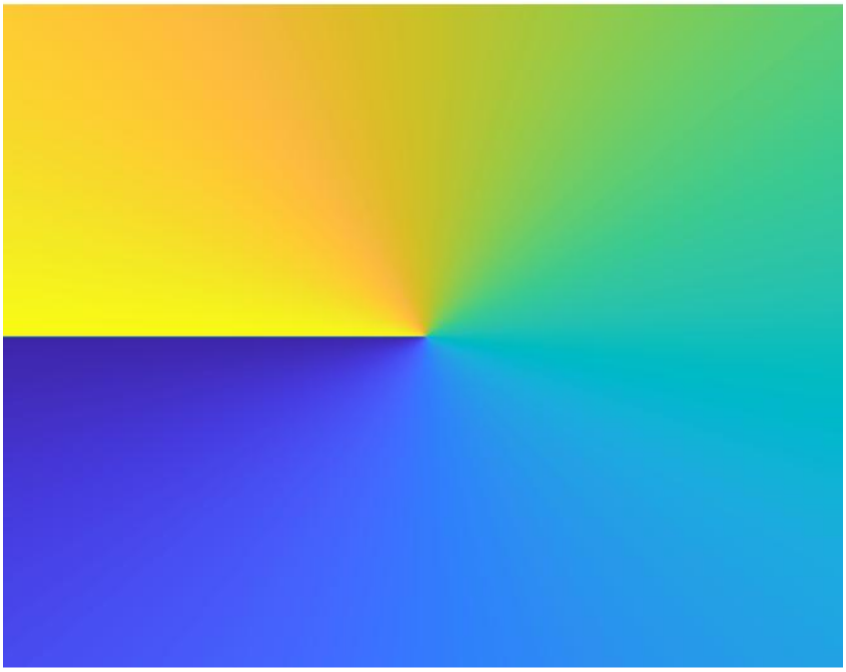


*fig 12:phase profile l=+5*

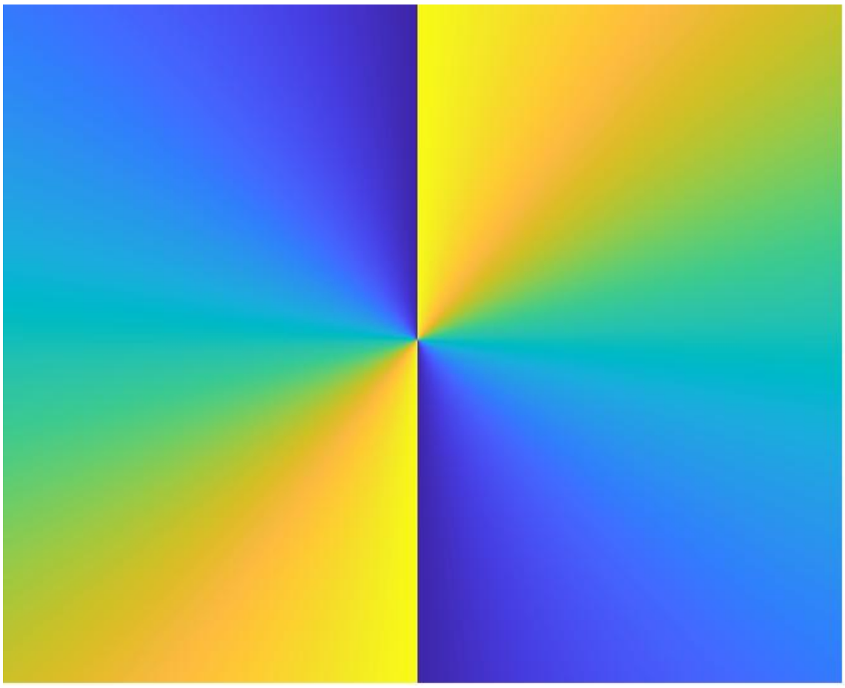


*fig 13:phase profile l=+7*

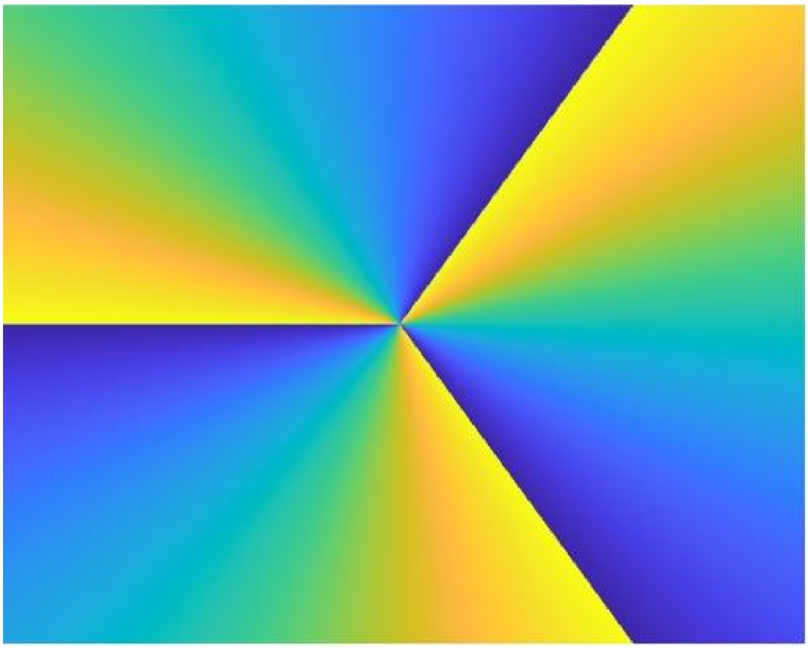


*fig 14:phase profile l=+3*

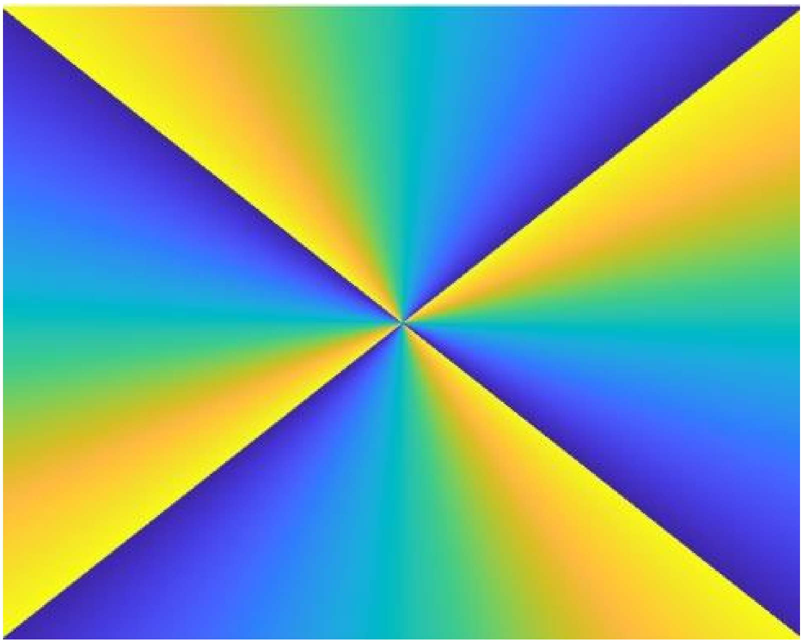


*fig 15:phase profile l=+8*

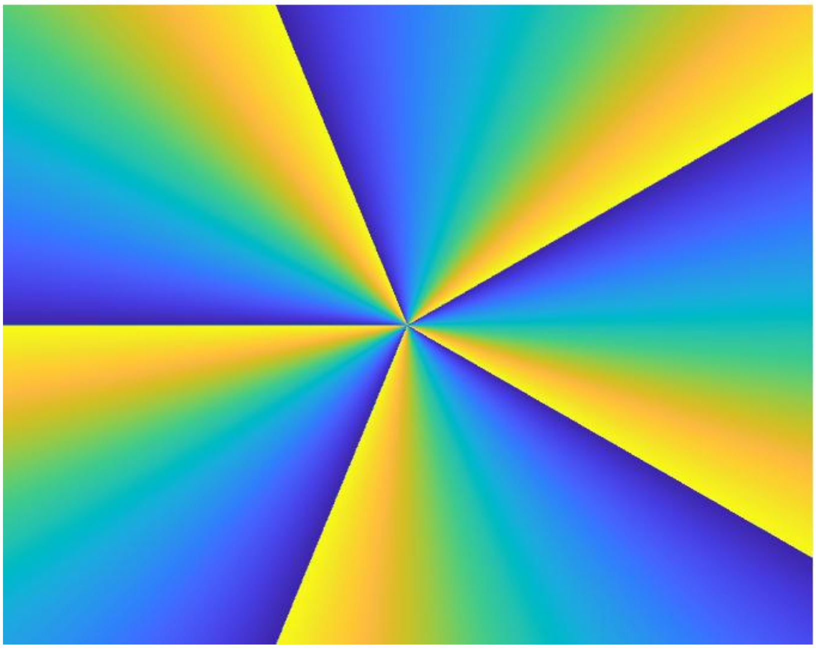


*fig 16:phase profile l=+6*

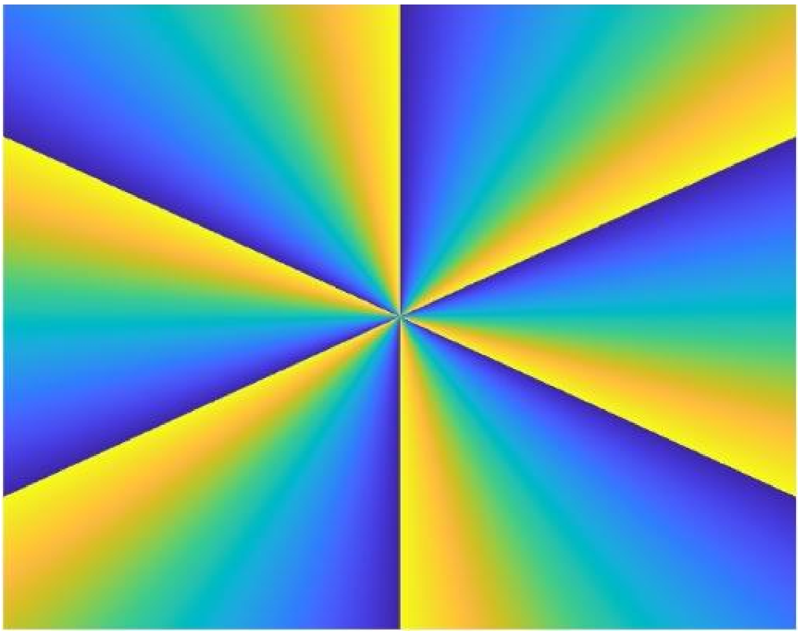


*fig 17:phase profile l=-9*

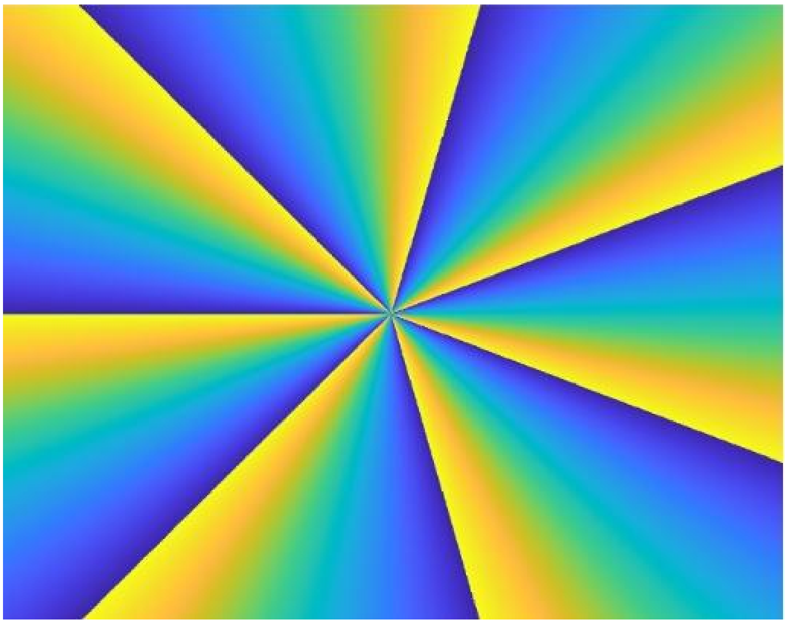


*fig 18:phase profile l=-4*

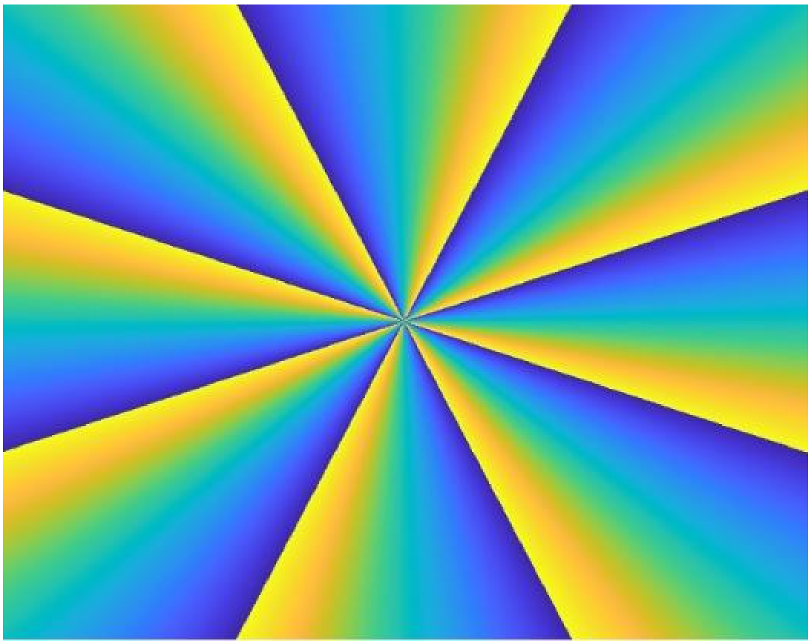


*fig 19:phase profile l=+2*

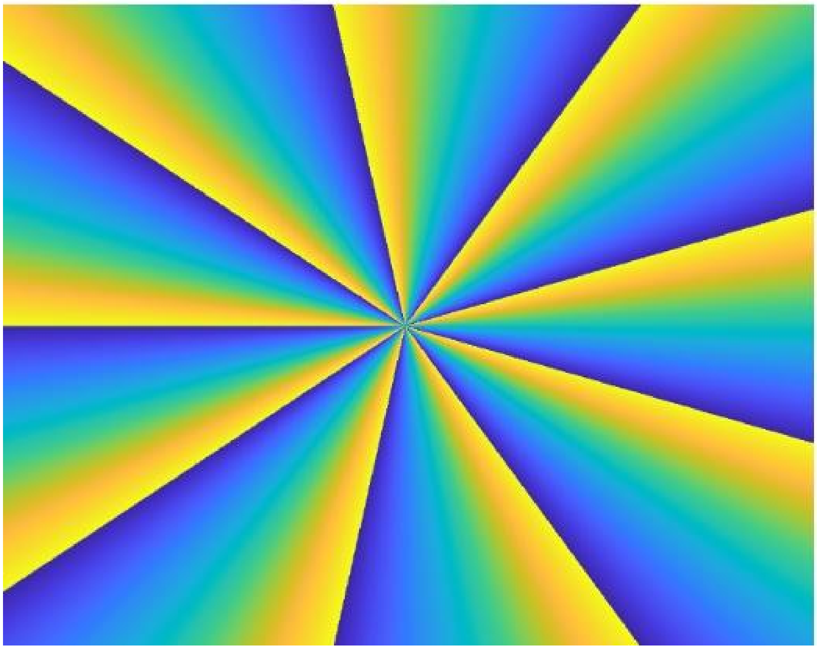


*fig 20:phase profile l=-5*

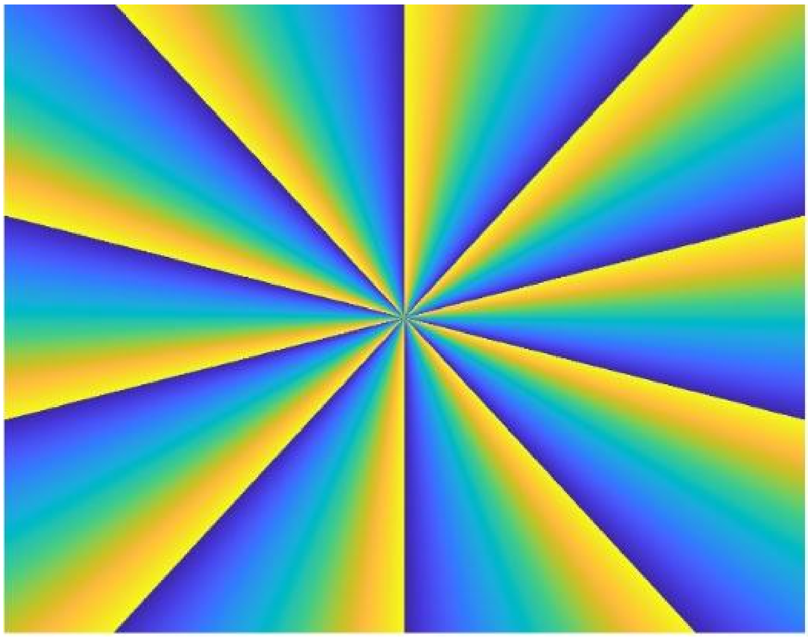


*fig 21:phase profile l=+4*

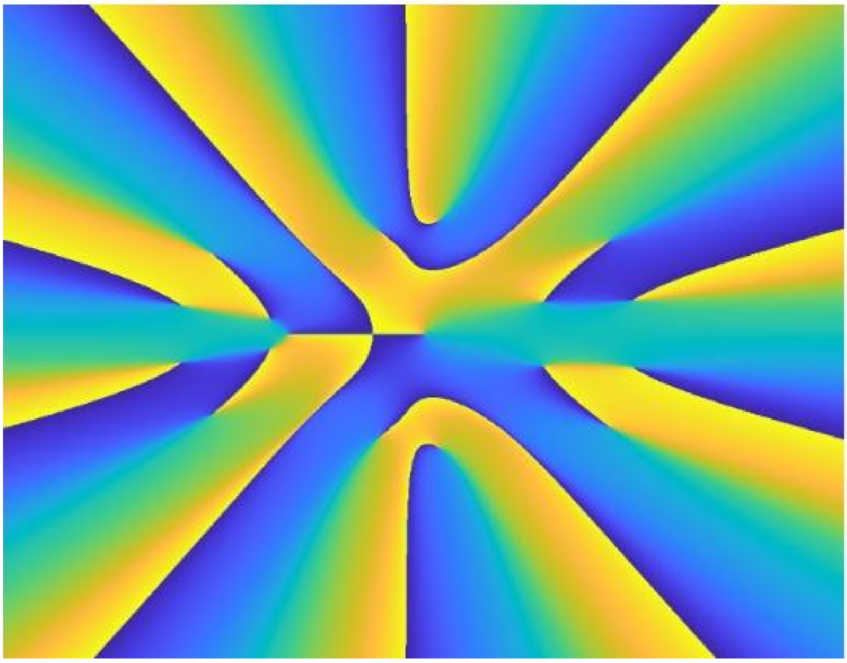


*fig 22: Multiplexed image*

### 3.2: Multiplexing of Lg beams

To meet the ever-increasing demands for higher data rates, researchers have explored various techniques for multiplexing data in multiple dimensions. Multiplexing of LG (Laguerre-Gaussian) beams refers to the process of encoding multiple data streams into different LG modes for transmission in optical communication systems. One such technique is Orbital Angular Momentum (OAM) multiplexing, which can be combined with different modulation formats and multiplexing techniques to achieve high-speed communication. In my project, I am utilising beams with a plate number of 1. Each beam consists of a set of modes ranging from -10 to +10, carrying modulation information for data. These beams are then combined into a single multimodal beam. Similarly, a second beam carrying a different class of modes is used to carry a different set of data, which is also multiplexed into another multimodal beam. This method allows for 10 classes of data to be included in one set, which comprises 10 multiplexed OAM beams. In total, we are using 8 sets of classes, which equates to 80 different multiplexed OAM beams. The obtained data sample set was then divided into a training set and a test set in a 7:3 ratio.

### 3.3: Demultiplexing the obtained data using SVM machine learning

Demultiplexing using Support Vector Machine (SVM) is a process that involves decoding and extracting individual data streams from a multiplexed signal encoded in Laguerre-Gaussian (LG) modes. This process can be divided into two phases: training and testing

During the training phase, a dataset is prepared which consists of multiplexed signals with known encoding and labels indicating the original data streams. Relevant features are extracted from these signals, such as amplitude, phase, frequency, or spatial characteristics, which can help differentiate between different LG modes or encoding schemes. The training dataset is then labelled according to the original data streams or LG modes they represent.

The SVM model is then trained using the labelled training dataset to learn the mapping between the extracted features and the corresponding data streams or LG modes. Once the model is trained, a separate test dataset is prepared consisting of multiplexed signals with unknown encoding. The same feature extraction methods used in the training phase are employed to extract features from the test signals.

The trained SVM model is then applied to predict the original data streams or LG modes represented by the test signals based on their extracted features. The model's performance is evaluated by comparing its predictions with the ground truth labels of the test dataset. Metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis are commonly used for this evaluation.

Image classification using Support Vector Machines (SVMs) involves training a model to classify images based on their features. To implement an SVM-based demultiplexing technique for image classification we need to follow the below steps

1. **Data Preparation**: Here we are collecting and preprocessing our image dataset. This involves resizing images to a uniform size, converting them to grayscale, or applying other transformations to enhance feature extraction.

2. **Data Splitting**: Splitting our dataset into training and testing sets. Allocating a significant portion of our dataset for training here we are giving 70% for training and the rest for testing i.e.30%.

3. **Model Training**: Train an SVM classifier using the extracted features and the training dataset. Using libraries fitcsvm function in MATLAB for this purpose.

4. **Model Evaluation**: Evaluate the trained SVM classifier using the testing dataset. Calculate performance metrics such as accuracy, precision, recall, and F1-score to assess its effectiveness in classifying images

## 3.4: SVM MACHINE LEARNING

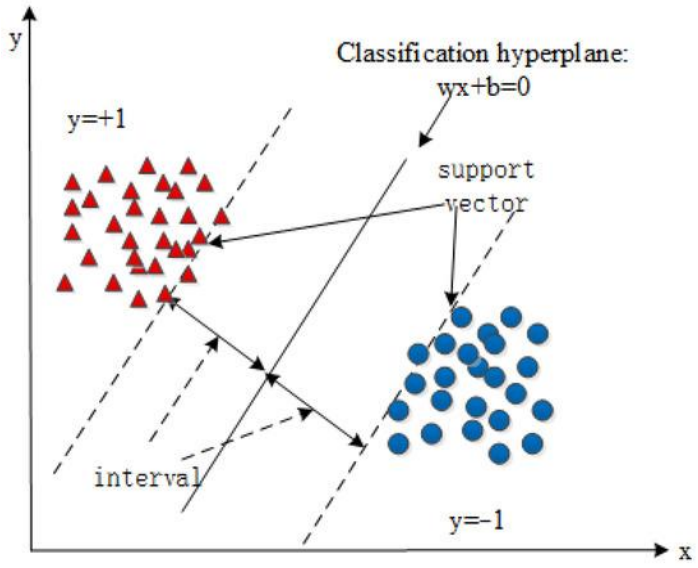
The demultiplexing process on the receiver side of the multiplexer involves training procedures that employ the support vector machine (SVM) algorithm. SVM is a robust machine learning algorithm that uses the kernel function to map data into a different dimensional space to group the information according to similar attributes. The raw data is fed into the algorithm as input, which is then classified depending on the kernel function. The data is then saved and compared with the original figure to identify similar patterns that are used for image identification. This iterative process continues until the maximum number of iterations n is reached, resulting in a simplification of complex nonlinear decision boundaries that are derived in a linear dimensional space. Mathematically speaking, the kernel used in the SVM algorithm for the proposed optical encoding model is the basis function (Gaussian).

## 3.5: BASIC PRINCIPLES OF SVM

Support Vector Machine (SVM) is a statistical model that classifies data. The key concept behind SVM is to locate the point that can bring all points closest to the hyperplane with the largest interval. In the figure below, the red triangular data points signify the class "y=+1" while the blue circular data points represent the class "y=-1". The SVM classification hyperplane that fits both data types can be expressed by the equation

$$f(x) = wTx + b$$

Here, w is the normal vector of the classification hyperplane, and b is the intercept. When f(x) is greater than or equal to 0, data point x belongs to class "y=+1". Conversely, data points where f(x) is less than 0 belong to class "y=-1". Therefore, by solving the variables w and b, we can obtain the maximum spacing hyperplane and classify data points in the plane.




Support Vector Machines (SVMs) have proved to be a suitable tool for image classification tasks. In order to apply SVMs for image classification, the first step involves extracting relevant features from the images. These features may include pixel intensity values, texture descriptors, colour histograms, or deep features extracted from pre-trained convolutional neural networks (CNNs). Once the features have been extracted, the data must be prepared for training and testing. This entails organising the feature vectors along with their corresponding labels into a format that is appropriate for training the SVM classifier. The SVM classifier can then be trained using the extracted features and their corresponding labels. One can utilise libraries such as scikit-learn in Python or LIBSVM in MATLAB to train SVM classifiers. Different kernel functions such as linear, polynomial, and RBF can be experimented with, along with hyperparameters, to discover the best-performing model.

Following the training of the SVM classifier, its performance can be evaluated using a separate validation or testing dataset. Accuracy, precision, recall, and F1-score are a few metrics that can be used to assess the classifier's performance in classifying images into different categories. After the SVM classifier has been trained and evaluated, it can be used to predict the class labels of new, unseen images. Fine-tuning the model may be required, depending on the performance of the initial SVM model. This process may involve adjusting hyperparameters, experimenting with different feature extraction methods, or trying various preprocessing techniques to further improve classification accuracy. Once the SVM model for image classification is satisfactory, it can be deployed for real-world applications. This could involve integrating the SVM model into a larger software system or deploying it as part of a web service or mobile application. It's important to note that while SVMs can be effective for image classification, they may not always perform as well as more complex deep learning models such as convolutional neural networks (CNNs), especially on large and complex datasets. Nonetheless, SVMs have the advantage of being simpler to implement and interpret, making them a good choice for certain image classification tasks, particularly when there are limitations in computational resources or when interpretability is crucial.

Support Vector Machines (SVMs) have emerged as a popular and effective tool for image classification tasks. In particular, SVMs have been successfully applied to demultiplexing OAM (Orbital Angular Momentum) beams, although other machine learning algorithms and signal processing techniques are also available for this purpose. SVMs offer several advantages that make them particularly well-suited for OAM demultiplexing. Firstly, SVMs can handle nonlinearity in classification tasks by using kernel functions, such as radial basis function (RBF) or polynomial kernels, which allow them to capture complex relationships in the data. Secondly, SVMs are known for their robustness to high-dimensional data, making them suitable for handling the complex data structures associated with OAM beams. Thirdly, SVMs aim to find the decision boundary (hyperplane) that maximises the margin between different classes in the feature space, which enables them to achieve better generalisation performance and robustness to noise. This is particularly crucial for accurate demultiplexing of OAM beams, especially in the presence of optical distortions and channel impairments.

### 3.6: Training for SVM-Based Demultiplexing Method

The data collected was divided into two sets to train the SVM-based demultiplexing method. The first set containing 60 different multiplexed images was used as a training set, while the second set with 20 different multiplexed images was used as a testing set. Both sets were completely independent of each other. The accuracy achieved was 70%. Once we have trained an SVM classifier and applied it to predict labels for a test dataset, we can use a confusion matrix to summarize the classifier's predictions against the true labels of the test data. The confusion matrix is a tool that is used to evaluate the performance of an SVM classifier and is closely related to SVM classification. A confusion matrix is a crucial tool used to evaluate the performance of a classification model. It is used after training an SVM classifier, which is then used to predict labels for a set of test data. The confusion matrix then summarizes the classifier's predictions in comparison to the true labels of the test data. Each entry of the confusion matrix represents the number of instances that were classified into a particular class by the SVM. It provides a detailed breakdown of how well a classification model is performing across different classes.

By examining the entries of the confusion matrix, one can identify where the model is making correct predictions, known as true positives (TP) and true negatives (TN), and where it's making errors, known as false positives (FP) and false negatives (FN). The true positives indicate that the classifier correctly classified the data instances that belong to a specific class, while true negatives indicate that the classifier correctly classified the data instances that do not belong to a specific class. False positives are instances that the classifier wrongly classified as belonging to a class when they do not, while false negatives are instances that the classifier wrongly classified as not belonging to a class when they do.

By analysing the entries of the confusion matrix, one can gain insights into the SVM classifier's strengths and weaknesses. For example, one can identify which classes are well-classified, as evidenced by high TP and TN instances, and which classes are frequently misclassified, as evidenced by high FP or FN instances. Additionally, one can determine where the model is performing well and where it requires improvement.

In summary, the confusion matrix provides a comprehensive overview of the classification performance of an SVM classifier, allowing for detailed analysis, evaluation, and refinement of the model. It serves as a valuable tool for assessing the classifier's accuracy, identifying problematic areas, and improving the model's performance.

Below are the *l* values which I have included in my project

*set1*

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 5 | 8 | 9 | -1 | -2 | -5 | -8 | 1 | 2 | Class 1 |
| 2 | 3 | 5 | 7 | -4 | -6 | -8 | -9 | 4 | 1 | Class2 |
| 3 | 6 | 5 | 4 | 2 | -2 | -5 | -3 | -7 | 1 | Class3 |
| 3 | 4 | 6 | 8 | 1 | -3 | -6 | -9 | 2 | -2 | Class4 |
| 1 | 2 | 3 | 4 | 5 | -1 | -2 | -3 | -4 | -5 | Class5 |
| 5 | 4 | 1 | 2 | 3 | -3 | -1 | -4 | -5 | -2 | Class6 |
| 6 | 7 | 8 | 9 | 10 | -10 | -9 | -7 | -8 | -6 | Class7 |
| 4 | 3 | 5 | 6 | 8 | -2 | -6 | 1 | -5 | 3 | Class8 |
| 9 | 8 | 5 | 6 | -2 | -3 | 7 | -4 | 1 | -1 | Class9 |
| 7 | 8 | -6 | 9 | 5 | 7 | 3 | -9 | 1 | -8 | Class10 |

*Set2*

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | Class 1 |
| 4 | 5 | 7 | 3 | -4 | -9 | 10 | 9 | 3 | 5 | Class2 |
| 6 | 7 | 8 | -4 | -6 | 2 | 9 | 8 | 5 | 2 | Class3 |
| 1 | -2 | 3 | -4 | 5 | -6 | 7 | 6 | 9 | -10 | Class4 |
| 6 | 4 | -9 | 8 | 3 | -2 | 2 | -8 | 10 | 6 | Class5 |
| 2 | 5 | -3 | -6 | -1 | 9 | 8 | 6 | 4 | 8 | Class6 |
| 10 | 9 | 8 | 7 | -9 | -7 | -5 | 5 | 2 | 1 | Class7 |
| 5 | 6 | 7 | 4 | 3 | -8 | -3 | -3 | 8 | 7 | Class8 |
| 8 | 7 | 6 | -3 | 8 | 9 | 4 | 4 | 1 | 4 | Class9 |
| 1 | 2 | 3 | 4 | -5 | -6 | -7 | 6 | 9 | 10 | Class10 |

*Set3*

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 5 | 7 | 3 | 8 | 6 | -9 | -4 | 2 | -5 | 4 | Class 1 |
| 7 | 4 | 9 | 5 | -9 | 8 | 7 | -6 | 5 | -4 | Class2 |
| 9 | 6 | 3 | -4 | 4 | 8 | 9 | 10 | 6 | -3 | Class3 |
| 1 | -9 | 2 | -7 | -9 | 2 | 10 | -3 | 5 | 6 | Class4 |
| -8 | 5 | -4 | 2 | 9 | -7 | -4 | -2 | -1 | 1 | Class5 |
| 9 | -5 | -7 | -9 | -1 | 9 | 8 | 5 | 4 | 8 | Class6 |
| 10 | 3 | 4 | 7 | -9 | -7 | -5 | -3 | 2 | 1 | Class7 |
| 6 | 2 | 8 | 5 | 5 | -6 | -2 | 6 | 7 | 4 | Class8 |
| 1 | -3 | 3 | -2 | 8 | 9 | 4 | 6 | 1 | 4 | Class9 |
| 6 | 8 | 3 | 7 | -5 | -6 | -7 | -8 | 9 | 10 | Class10 |

*Set4*

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 6 | 8 | 3 | -7 | -2 | -1 | -10 | 5 | 2 | 9 | Class 1 |
| 3 | 2 | -9 | -5 | 9 | 3 | 1 | -8 | 10 | -6 | Class2 |
| 4 | 6 | 8 | -2 | 4 | 5 | 6 | -10 | -6 | -8 | Class3 |
| 10 | 8 | 2 | -3 | -7 | 2 | -10 | -1 | 9 | 6 | Class4 |
| 5 | -4 | 2 | 9 | -7 | -4 | -2 | -10 | 6 | 9 | Class5 |
| 8 | -2 | -6 | -1 | 1 | -9 | -8 | 7 | 3 | 8 | Class6 |
| 1 | 9 | 2 | 5 | 7 | -7 | 8 | -2 | 10 | -1 | Class7 |
| 5 | 3 | 9 | 6 | -4 | -5 | -3 | 8 | 7 | 5 | Class8 |
| 1 | 6 | -2 | -5 | 7 | -10 | 5 | -9 | 5 | 8 | Class9 |
| 1 | -5 | 6 | 8 | 10 | -9 | 4 | -8 | -4 | 1 | Class10 |

*Set5*

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 7 | 9 | 4 | -6 | -3 | -2 | -1 | 6 | 3 | 10 | Class 1 |
| 4 | 3 | -5 | -6 | 10 | 4 | 5 | -8 | 2 | -7 | Class2 |
| 5 | 7 | 9 | -3 | 5 | 6 | 7 | -1 | -4 | 4 | Class3 |
| 1 | 9 | 3 | -2 | -8 | 3 | -1 | -10 | 6 | 3 | Class4 |
| 6 | -5 | 3 | 8 | -6 | -3 | -1 | -9 | 5 | 8 | Class5 |
| 9 | -3 | -9 | -1 | 1 | 2 | -8 | 7 | 3 | 8 | Class6 |
| 2 | 10 | 3 | 6 | 8 | -8 | -6 | -3 | 7 | -10 | Class7 |
| 6 | 4 | 10 | 7 | -5 | -6 | -4 | 9 | 8 | -10 | Class8 |
| 10 | 7 | -3 | -4 | 8 | -1 | 6 | -9 | 2 | 9 | Class9 |
| 2 | -6 | 8 | 9 | 1 | -10 | 5 | -9 | -5 | 1 | Class10 |

*Set6*

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 8 | 10 | 5 | -7 | -4 | -3 | -2 | 7 | 2 | 1 | Class 1 |
| 5 | 4 | -6 | -7 | 1 | 5 | 7 | -9 | 3 | -8 | Class2 |
| 6 | 8 | 10 | 4 | 6 | 7 | 8 | -2 | -5 | 5 | Class3 |
| 2 | 10 | 4 | -3 | -9 | 4 | -2 | -1 | 7 | 4 | Class4 |
| 6 | -5 | 3 | 8 | -6 | -3 | -1 | -10 | 7 | 10 | Class5 |
| 10 | -4 | -3 | -2 | 2 | 3 | -9 | 8 | 4 | 9 | Class6 |
| 3 | 1 | 4 | 7 | 9 | -8 | -6 | -4 | 8 | -1 | Class7 |
| 7 | 5 | 1 | 8 | -6 | -7 | -5 | 10 | 4 | -1 | Class8 |
| 1 | 8 | -4 | -5 | 9 | -8 | 7 | -9 | 3 | 10 | Class9 |
| 3 | -7 | 9 | 10 | 5 | 7 | -3 | -10 | 2 | 1 | Class10 |

*Set7*

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 5 | 7 | -9 | -5 | -1 | 10 | 9 | 8 | 6 | Class1 |
| 4 | 6 | 7 | -9 | -1 | -3 | 5 | 7 | 1 | 5 | Class2 |
| 9 | 8 | 7 | 6 | 4 | 5 | -9 | -4 | 7 | -2 | Class3 |
| 7 | 8 | 9 | 10 | -1 | -3 | -2 | -6 | 8 | -5 | Class4 |
| 9 | 8 | -2 | -4 | -1 | -10 | 5 | 6 | 10 | 1 | Class5 |
| 7 | 6 | 8 | 9 | 10 | 2 | 5 | -3 | -8 | -1 | Class6 |
| 9 | 5 | 6 | -2 | -9 | -4 | -1 | 5 | 6 | 3 | Class7 |
| -1 | -2 | -3 | -4 | 5 | 6 | 7 | 8 | -9 | -10 | Class8 |
| 8 | 9 | 6 | -2 | 10 | 3 | -2 | -5 | -1 | -9 | Class9 |
| 1 | 2 | 3 | 4 | -5 | -6 | -7 | -8 | 9 | 10 | Class10 |

*Set8*

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 9 | 8 | 5 | 4 | -2 | -4 | 1 | -10 | 7 | 10 | Class1 |
| 10 | -3 | 9 | 4 | 7 | -8 | -1 | -5 | 2 | -7 | Class2 |
| 4 | 5 | 8 | 10 | 3 | 6 | -9 | -3 | 2 | 6 | Class3 |
| 1 | 2 | -3 | -4 | 5 | 6 | -7 | -2 | 9 | 10 | Class4 |
| 9 | -8 | -5 | -3 | 2 | 1 | 6 | 3 | 10 | 6 | Class5 |
| 8 | 7 | 9 | 10 | -3 | -4 | 10 | -2 | -8 | 4 | Class6 |
| 10 | 6 | 7 | -1 | -2 | -6 | 8 | -4 | 2 | 3 | Class7 |
| 1 | 3 | 5 | 7 | -9 | -8 | -2 | -4 | 2 | 4 | Class8 |
| 8 | 3 | 2 | -2 | 4 | 1 | 6 | -6 | 9 | 5 | Class9 |
| 9 | 8 | 2 | -2 | 1 | -9 | -1 | 4 | 8 | -6 | Class10 |

# 4: ANALYSIS AND CONCLUSION

In the initial phase of my project, I focused on generating a diverse range of values for the Orbital Angular Momentum (OAM) modes. Once I had collected these modes, my next task was to multiplex these beams, which involved combining them into a single beam. After that, I needed to demultiplex the intensity beam using machine learning. This process involved training and testing the datasets where I divided my 80 multiplexed beams in the ratio 60:20, i.e., 60 images belong to the training set and the remaining 20 images belong to the testing set. The primary objective of this step was to achieve the best possible accuracy. I was able to achieve an accuracy of 56.67% for four sets (40 multiplexed beams), where I grouped them into two. However, the accuracy I achieved for 80 multiplexed images was 70%, which was quite impressive. Additionally, I was able to obtain multiplexed images of the phase profile For total 60 images of which 45 were training and 15 were testing, the accuracy I achieved was 80 % . To evaluate the performance of my model, I created confusion matrices for the accuracy of 56.67% ,70%, and 80% respectively. Overall, these results demonstrate that my model was successful in achieving high accuracy in the demultiplexing of intensity and phase beams.

The confusion matrix presented below depicts an accuracy rate of 70% for my testing data, where my 60 images were for training and 20 were for testing, which is divided into two classes - class 1 and class 2. The matrix provides insights into how the predicted outcomes compare to the actual results.

For class 1, out of a total of 14 images, 12 are true positives, meaning that they were correctly predicted to belong to class 1. Additionally, 2 images are true negatives, which means that they were correctly predicted to not belong to class 1.

On the other hand, for class 2, out of a total of 6 images, 4 are false positives, meaning that they were incorrectly predicted to belong to class 2. The remaining 2 images are false negatives, indicating that they were incorrectly predicted to not belong to class 2.

Overall, out of the 20 testing images, 14 were correctly classified into their respective classes. It is important to analyse the confusion matrix in order to identify any patterns or trends that can help improve the accuracy of future predictions.

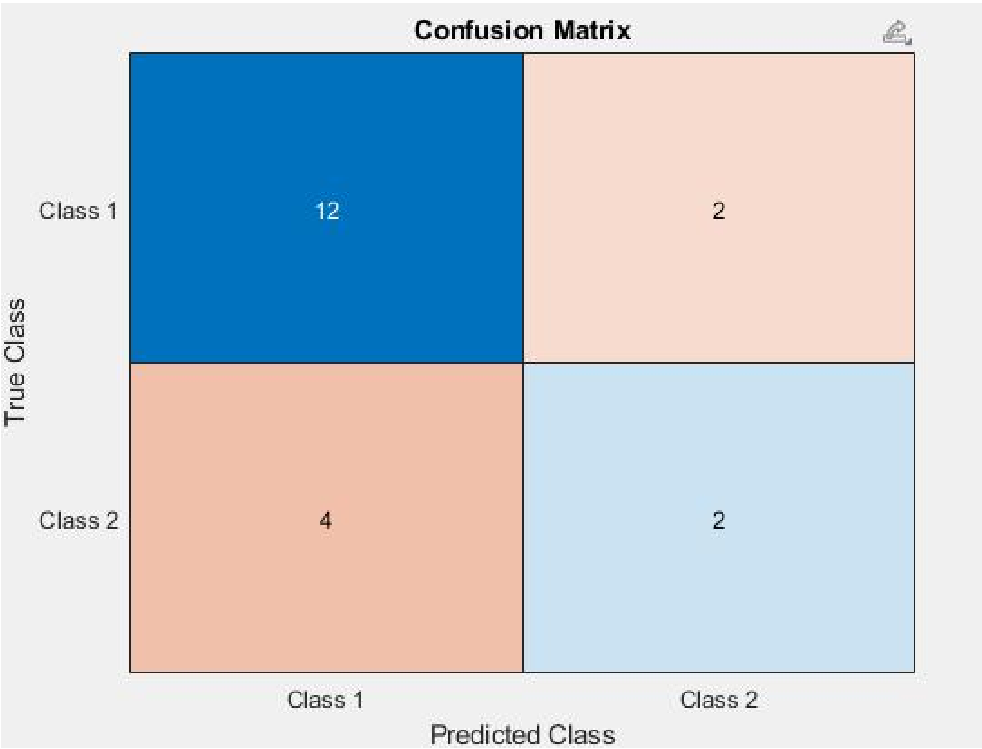
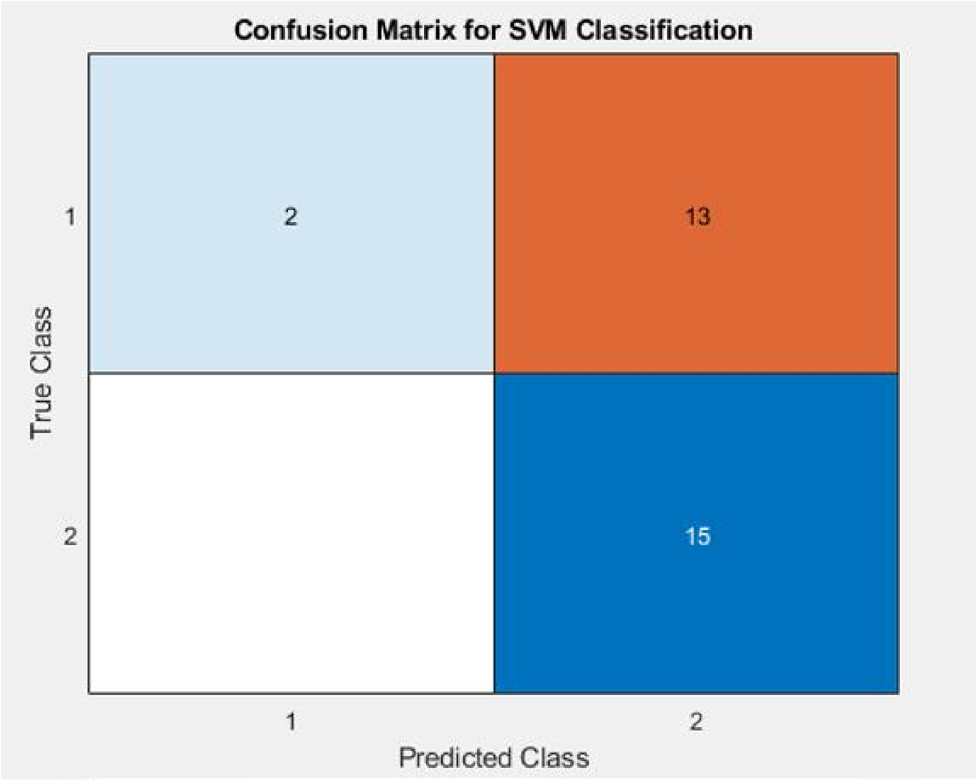
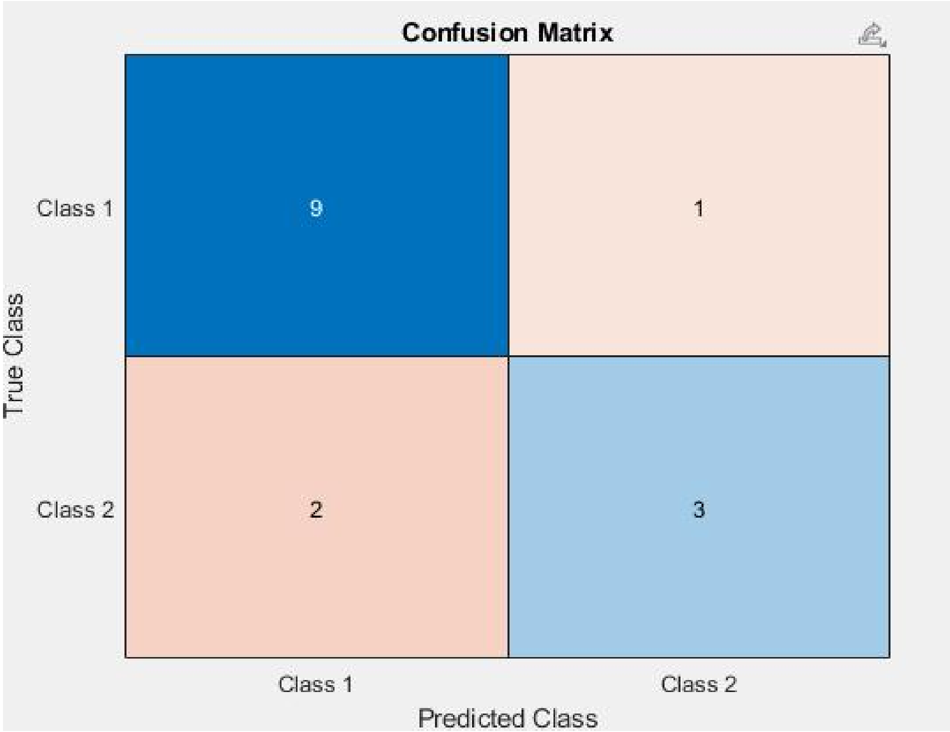



*fig 1*




Based on the above provided information, it can be inferred that the data was divided into two classes, class1 and class2, with a total of 30 testing images. The accuracy of the confusion matrix was determined to be 56.67%, which is a measure of how well the model predicted the correct class for the testing images. Out of the 30 images, 2 images were correctly predicted to be in class1, while 13 images were correctly predicted to not be in class2. However, out of the remaining 15 images in class2, 0 are false positives, meaning that they were incorrectly predicted to belong to class 2. The remaining 15 images are false negatives, indicating that they were incorrectly predicted to not belong to class 2. Overall, the model was able to accurately classify 17 out of the 30 testing images.




The above confusion matrix is of phase multiplexed image where I am having total 60 images which I have divided into ratio 45:15 .so in class 1 out of 10 images my 9 images were correctly predicted to be in class 1, Additionally, 1 image is true negative, which means that they were correctly predicted to not belong to class 1.

On the other hand, for class 2, out of a total of 5 images, 2 are false positives, meaning that they were incorrectly predicted to belong to class 2. The remaining 3 images are false negatives, indicating that they were incorrectly predicted to not belong to class 2.

## CONCLUSION:

In recent project, we proposed and demonstrated a novel method that utilizes the Support Vector Machine (SVM) theory of machine-learning to detect the Orbital Angular Momentum (OAM) beam. The results obtained from extensive simulations were found to be highly promising. Our study focused on the classification of OAM based on detection accuracy, with an aim to identify the most effective approach for accurately detecting and identifying OAM beams.

Our findings revealed that the accuracy of the OAM beam detection gradually increased with the use of more OAM images. This suggests that the more OAM images are utilized, the more accurately the OAM beam can be identified. Additionally, we found that the accuracy of the OAM beam detection also depends on the splitting of the data into training and testing phases.

The significance of this new method and its potential applications cannot be understated. Accurate detection and identification of OAM beams are vital in numerous fields, including but not limited to optical communication, astronomy, and remote sensing. Our proposed method could be particularly useful in these fields and beyond, where the reliable characterization of OAM beams is critical.

4.1 REFRENCES


1. Gibson, Graham, et al. “Free-Space Information Transfer Using Light Beams Carrying Orbital Angular Momentum.” *Optics Express*, vol. 12, no. 22, 2004, p. 5448, https://doi.org/10.1364/opex.12.005448. Accessed 30 Nov. 2020.
2. Fatkhiev, Denis M., et al. “Recent Advances in Generation and Detection of Orbital Angular Momentum Optical Beams—a Review.” *Sensors*, vol. 21, no. 15, 22 July 2021, p. 4988, https://doi.org/10.3390/s21154988. Accessed 2 Mar. 2023.
3. Zhu, Fuquan, et al. “Free-Space Optical Communication Link Using Perfect Vortex Beams Carrying Orbital Angular Momentum (OAM).” *Optics Communications*, vol. 396, Aug. 2017, pp. 50–57, https://doi.org/10.1016/j.optcom.2017.03.023. Accessed 30 Nov. 2020.
4. Gong Yinghui, et al. *Generation and Transmission of OAM-Carrying Vortex Beams Using Circular Antenna Array*. Vol. 65, no. 6, 1 June 2017, pp. 2940–2949, https://doi.org/10.1109/tap.2017.2695526. Accessed 1 July 2023.
5. Giordani, Taira, et al. “Machine Learning-Based Classification of Vector Vortex Beams.” *Physical Review Letters*, vol. 124, no. 16, 20 Apr. 2020, https://doi.org/10.1103/physrevlett.124.160401. Accessed 9 Dec. 2023.
6. Wang, Yue, et al. “Orbital Angular Momentum Multiplexing Holography Based on Multiple Polarisation Channel Meta surface Nanophononics vol. 12, no. 23, 2 Nov. 2023, pp. 4339–4349, https://doi.org/10.1515/nanoph-2023-0550. Accessed 17 Mar. 2024.
7. Chen, Xiaoming, et al. “Orbital Angular Momentum Multiplexing in Highly Reverberant Environments.” *IEEE Microwave and Wireless Components Letters*, vol. 30, no. 1, Jan. 2020, pp. 112–115, https://doi.org/10.1109/lmwc.2019.2952975. Accessed 13 Mar. 2023.

8. Yan, Yan, et al. “High-Capacity Millimetre-Wave Communications with Orbital Angular Momentum Multiplexing.” *Nature Communications*, vol. 5, no. 1, 16 Sept. 2014, https://doi.org/10.1038/ncomms5876. Accessed 5 Apr. 2022.
9. Paroli, B., et al. “Hybrid OAM-Amplitude Multiplexing and Demultiplexing of Incoherent Optical States.” *Optics Communications*, vol. 524, Dec. 2022, p. 128808, https://doi.org/10.1016/j.optcom.2022.128808. Accessed 9 Mar. 2023.
10. Wang, Jian. “Advances in Communications Using Optical Vortices.” *Photonics Research*, vol. 4, no. 5, 1 Sept. 2016, p. B14, https://doi.org/10.1364/prj.4.000b14. Accessed 14 Aug. 2022.
11. Wang, Xiaohui, et al. “Synthesising the Crosstalk between OAM Modes of Vortex Beam by Simultaneously Propagating a Probe Vortex Beam in Free Space.” *Optics & Laser Technology/Optics and Laser Technology*, vol. 165, 1 Oct. 2023, pp. 109622–109622, https://doi.org/10.1016/j.optlastec.2023.109622. Accessed 3 May 2024.
12. Doster, Timothy, and Abbie T Watnik. *Machine Learning Approach to OAM Beam Demultiplexing via Convolutional Neural Networks*. Vol. 56, no. 12, 20 Apr. 2017, pp. 3386–3386, https://doi.org/10.1364/ao.56.003386. Accessed 20 May 2023.
13. Sun, RiDong, et al. “Identifying Orbital Angular Momentum Modes in Turbulence with High Accuracy via Machine Learning.” *Journal of Optics*, vol. 21, no. 7, 12 June 2019, pp. 075703–075703, https://doi.org/10.1088/2040-8986/ab2586. Accessed 3 May 2024.
14. Wang, Peipei, et al. “Diffractive Deep Neural Network for Optical Orbital Angular Momentum Multiplexing and Demultiplexing.” *IEEE Journal of Selected Topics in Quantum Electronics*, vol. 28, no. 4, 1 July 2022, pp. 1–11, https://doi.org/10.1109/jstqe.2021.3077907. Accessed 3 May 2024.

15. Gong, Lei, et al. "Optical Orbital-Angular-Momentum-Multiplexed Data Transmission under High Scattering." *Light: Science & Applications*, vol. 8, no. 1, 6 Mar. 2019, https://doi.org/10.1038/s41377-019-0140-3. Accessed 8 Dec. 2022.
16. Lamilla, Erick, et al. "Optical Encoding Model Based on Orbital Angular Momentum Powered by Machine Learning." *Sensors*, vol. 23, no. 5, 2 Mar. 2023, pp. 2755–2755, https://doi.org/10.3390/s23052755. Accessed 3 May 2024.
17. Li, Xiaoji, et al. "Identification of Orbital Angular Momentum by Support Vector Machine in Ocean Turbulence." *Journal of Marine Science and Engineering*, vol. 10, no. 9, 12 Sep. 2022, pp. 1284–1284, https://doi.org/10.3390/jmse10091284. Accessed 3 May 2024.
18. Chen, Rui, et al. "Orbital Angular Momentum Waves: Generation, Detection, and Emerging Applications." *IEEE Communications Surveys & Tutorials*, vol. 22, no. 2, 2020, pp. 840–868, https://doi.org/10.1109/comst.2019.2952453.
19. Allen, L., et al. "Orbital Angular Momentum of Light and the Transformation of Laguerre-Gaussian Laser Modes." *Physical Review A*, vol. 45, no. 11, 1 June 1992, pp. 8185–8189, https://doi.org/10.1103/physreva.45.8185.
20. Berkhout, Gregorius C. G., et al. "Efficient Sorting of Orbital Angular Momentum States of Light." *Physical Review Letters*, vol. 105, no. 15, 4 Oct. 2010, https://doi.org/10.1103/physrevlett.105.153601.
21. Fu, Shiyao, et al. "Measurement of Orbital Angular Momentum Spectra of Multiplexing Optical Vortices." *Optics Express*, vol. 24, no. 6, 11 Mar. 2016, pp. 6240–6240, https://doi.org/10.1364/oe.24.006240. Accessed 3 May 2024.
22. Cui, Xiao-zhou, et al. "Analysis of an Adaptive Orbital Angular Momentum Shift Keying Decoder Based on Machine Learning under Oceanic Turbulence Channels."

*Optics Communications*, vol. 429, 1 Dec. 2018, pp. 138–143, https://doi.org/10.1016/j.optcom.2018.08.011. Accessed 3 May 2024.

23. Xiong, Wenjie, et al. “Convolutional Neural Network Assisted Optical Orbital Angular Momentum Identification of Vortex Beams.” *IEEE Access*, vol. 8, 1 Jan. 2020, pp. 193801–193812, https://doi.org/10.1109/access.2020.3029139. Accessed 18 Mar. 2024.
24. Zhang, Kuang, et al. “A Review of Orbital Angular Momentum Vortex Beams Generation: From Traditional Methods to Meta surfaces.” *Applied Sciences*, vol. 10, no. 3, 1 Jan. 2020, p. 1015, www.mdpi.com/632614, https://doi.org/10.3390/app10031015. Accessed 27 Apr. 2023.
25. Ye, J., Belal Jahannia, Kang, H., Wang, H., Heidari, E., Navid Asadizanjani, Sorger, V. and Hamed Dalir (2024). OAM modes classification and demultiplexing via Fourier optical neural network. doi https:/ doi.org/10.1117/12.3003172.
26. Zhang, Kuo, et al. “Advanced All-Optical Classification Using Orbital-Angular-Momentum-Encoded Diffractive Networks.” *Adv. Photonics Nexus*, vol. 2, no. 06, 26 Nov. 2023, https://doi.org/10.1117/1.apn.2.6.066006. Accessed 6 May 2024.
27. Lin, Tianying, et al. “Analysing OAM Mode Purity in Optical Fibers with CNN-Based Deep Learning.” *Chinese Optics Letters*, vol. 17, no. 10, 2019, p. 100603, https://doi.org/10.3788/col201917.100603. Accessed 6 Mar. 2020.
28. Stankevich, Dmitry. *Orbital Angular Momentum Acoustic Modes Demultiplexing by Machine Learning Methods*. 1 Jan. 2019, https://doi.org/10.18287/1613-0073-2019-2416-300-307. Accessed 7 May 2024.
29. Neary, Patrick L., et al. “Machine Learning-Based Signal Degradation Models for Attenuated Underwater Optical Communication OAM Beams.” *Optics*

*Communications*, vol. 474, Nov. 2020, p. 126058, https://doi.org/10.1016/j.optcom.2020.126058. Accessed 6 Nov. 2020.

30. Lohani, Sanjaya, et al. "On the Use of Deep Neural Networks in Optical Communications." *Applied Optics*, vol. 57, no. 15, 16 May 2018, p. 4180, https://doi.org/10.1364/ao.57.004180. Accessed 15 Apr. 2022.
31. Giordani, Taira, et al. "Machine Learning-Based Classification of Vector Vortex Beams." *Physical Review Letters*, vol. 124, no. 16, 20 Apr. 2020, https://doi.org/10.1103/physrevlett.124.160401. Accessed 9 Dec. 2023.
32. Khan, Faisal Nadeem, et al. "An Optical Communication's Perspective on Machine Learning and Its Applications." *Journal of Lightwave Technology*, vol. 37, no. 2, 1 Jan. 2019, pp. 493–516, ieeexplore.ieee.org/abstract/document/8633908/, https://doi.org/10.1109/JLT.2019.2897313.
33. Ma, Rui, et al. "Orbital-Angular-Momentum Dependent Speckles for Spatial Mode Sorting and Demultiplexing." *Optica*, 3 Apr. 2024, https://doi.org/10.1364/optica.523846. Accessed 7 May 2024.