MULTISPECTRAL APPROACH FOR EGG QUALITY CHECK

A Dissertation for

Course code and Course Title: ELE-625 Project

Credits: 16

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

Mr. Vishal Pravin Jagtap

Seat No.: 22P0360008

ABC ID: 847960354618

PR NO: 201801850

Under the Supervision of

Dr. Aniketh Gaonkar

School of Physical and Applied Sciences

Electronics

GOA UNIVERSITY
MAY 2024

School of Physical and Applied Sciences Goa University

Examined by:

Seal of the School

DECLARATION BY STUDENT

I hereby declare that the data presented in this Dissertation report entitled, Multispectral Approach For Egg Quality Check based on the results of investigations carried out by me in the M.Sc Electronics at the School of Physical and Applied Sciences, Goa University under the Supervision of Dr. Aniketh Gaonkar 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 any one as needed.

Name of Student: Vishal Jagtap
Signature

Seat no: 22P0360008

Date:
Place: Goa University

COMPLETION CERTIFICATE

This is to certify that the dissertation report Multispectral Approach For Egg Quality Check is a bonafide work carried out by Mr. Vishal Jagtap under my supervision in partial fulfillment 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. Aniketh Gaonkar

School of Physical and Applied Sciences

Goa University

Date:

Prof Ramesh V. Pai

School of Physical and Applied Sciences

School of Physical and Applied Sciences Goa University

School Stamp

Date:

Place: Goa University

TABLE OF CONTENTS

PREFACE

This dissertation represents the culmination of several months of research and hard work, and it is with great pleasure that I present it to the academic community.

Throughout this journey, I have been fortunate to receive support and guidance from many individuals and institutions, to whom I owe immense gratitude.

The dissertation is organized as follows: Chapter 1 provides an introduction to the topic, including its significance and relevance. Chapter 2 reviews the existing literature on the Multispectral Approach For Egg Quality Check of freshness of good and bad eggs synthesizing key findings and identifying gaps in the literature. Chapter 3 deals with the Database generation and acquisition protocols. Chapter 4 outlines the methodology employed in this study, detailing the research design, and analytical approach. Finally, Chapter 5 presents the empirical findings through Experimental evaluation and results.

Acknowledgment

I would like to express my sincerest thanks to everyone who has contributed to this project.

First and foremost, I would like to thank Dr. Aniketh Gaonkar for his guidance and have provided me with their time

I express my deep gratitude towards all the teaching faculty Prof. Rajendra S. Gad, Prof. Jivan. S. Parab, Dr. Marlon Sequeira, Dr. Narayan Vetrekar, and Dr. Sandip 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.

A sincere thanks to Miss Krishna, Miss Marrisa, Mrs. Ashwini, Sir. Ramchandra, Sir. Vishant and Sir. Lopes for their constand help and support throughout this project.

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

“MULTISPECTRAL APPROACH FOR EGG QUALITY CHECK”

Vishal Jagtap
Electronics Discipline, SPAS
Goa University

Abstract

The present project report provides an in-depth exploration of the utilization of multispectral imaging technology for the comprehensive assessment of egg quality. Multispectral imaging, characterized by the capture of images at multiple wavelengths of light, facilitates the extraction of detailed information regarding the physical and chemical properties of eggs. This technique enables the evaluation of egg freshness, the detection of cracks, and the overall assessment of quality without causing any damage to the eggs.

The primary objective of this research is to develop a reliable and efficient method for egg quality inspection, with the potential to significantly enhance current practices in the poultry industry. Through the analysis of spectral data, subtle differences in egg composition and structure, imperceptible to the naked eye, can be identified. The implementation of this technology ensures that only high-quality, safe eggs reach consumers, consequently augmenting food safety and quality control measures.

The findings of this study underscore the potential of multispectral imaging as a potent tool for non-invasive egg quality assessment. This approach not only expedites the inspection process but also diminishes the likelihood of human error, thereby yielding more consistent and accurate results. The implications of this research are substantial, offering a technological advancement that can be seamlessly integrated into existing quality control systems within the poultry industry.

Table and Figures

Abbreviation

Entity	Abbreviation
Machine Learning	ML
Convolutional Neural Networks	CNN
k-Nearest Neighbors	KN
Analytical Research	AR
Support Vector Machine	SVM

CHAPTER-1

I N T R O D U C T I O N

1. Introduction

The traditional approach to egg quality assessment in the poultry industry has been through manual checks and candling. This method is often time-consuming and subjective, which can result in inconsistent egg quality and unnecessary waste of perfectly good eggs. However, with advancements in image processing technology, egg quality assessment is being revolutionized.

Image processing technology has made it possible to predict egg freshness and nutritional value accurately. This technology relies on sensors such as cameras and microphones to examine eggs and assess their quality based on factors such as shell integrity, air cell size, yolk color, and sound. Machine learning algorithms can then analyze the data collected by the sensors and categorize the eggs as good, bad, or intermediate, based on predefined criteria.

The use of image processing technology in egg quality assessment offers several advantages over traditional methods. Firstly, it improves food safety and quality by identifying eggs that may be contaminated with Salmonella or other pathogens that can cause foodborne illnesses. Secondly, it reduces waste by identifying eggs that are not fit for consumption before they reach the market. This helps to increase the profit margin for egg producers by minimizing food waste and ensuring that only high-quality eggs are sold to consumers.

Moreover, image processing technology can also enhance the nutritional value of eggs by predicting the nutritional content of each egg. By analyzing data such as yolk color, the technology can predict the nutrient content of eggs, such as protein, omega-3 fatty acids, and other essential nutrients. This information can help producers to market their eggs as high-quality and nutritious, which can increase consumer demand and profitability.

Overall, the use of image processing technology in egg quality assessment has the potential to revolutionize the poultry industry. It improves food safety and quality, reduces waste, and enhances the nutritional value of eggs. By incorporating these advancements into their operations, egg producers can increase their profitability while also providing high-quality and nutritious eggs to consumers.

1.1 Image processing

Image processing is a field that encompasses a variety of disciplines and techniques, all of which revolve around the manipulation, analysis, and interpretation of digital images. This multidisciplinary approach is used to enhance, transform, and extract meaningful information from images, which can then be applied to a wide range of fields. The techniques and algorithms used in image processing are constantly evolving and improving, and they play a crucial role in modern scientific research and technological advancements. Overall, image processing is an important and complex field that requires a deep understanding of both the theoretical and practical aspects involved.

Definition and Scope:

The term "image processing" refers to the application of mathematical, statistical, and computational techniques to digital images in order to improve their quality, extract relevant information, or adapt them to specific applications. This complex process involves the manipulation of both visual and non-visual aspects of the image, with the aim of enhancing its overall appearance, as well as extracting quantitative data. The scope of image processing is vast and encompasses a wide range of fields, including medical imaging, remote sensing, and computer vision, among others. Its theoretical underpinnings draw heavily from mathematics, computer science, and engineering, and its practical applications continue to expand and evolve with advances in technology.

There are two primary types of image processing, each with its own unique characteristics and applications. The first type, known as analog image processing, involves manipulating physical photographs or film negatives through techniques such as cropping, filtering, and color correction. While this method was once prevalent, it has become far less common with the widespread adoption of digital technology. The second type of image processing is digital image processing, which involves the manipulation of images that are represented as arrays of numerical values, or pixels. This process utilizes algorithms that are implemented on computers and can encompass a wide range of operations, including filtering, edge detection, segmentation, feature extraction, and image restoration. Digital image processing has become increasingly important in a variety of fields, including medical imaging, remote sensing, and computer vision, among others. Its applications continue to grow and evolve as new technologies and techniques emerge.

In the field of image processing, a number of fundamental operations are routinely employed in order to manipulate and analyze digital images. These operations can be broadly classified into several distinct categories, each with its own specific techniques and objectives. The first category of operations is image acquisition, which involves the capture of images using cameras, scanners, or other imaging devices. Once acquired, these images are then subjected to a series of preprocessing steps, including noise reduction, contrast enhancement, and image resizing, in order to prepare them for further analysis. Image enhancement techniques are then employed to improve the visual quality of images, such as sharpening, brightness adjustment, and color correction. Restoration methods are also utilized to remove or reduce degradation caused by noise, blurring, or other artifacts. Feature extraction is another important operation in image processing, which involves the identification and extraction of meaningful features from images, such as edges, corners, textures, or regions of interest. Image segmentation is then employed to partition an image into meaningful regions or objects based on similarities in intensity, color, or texture. Finally, object recognition and classification is used to identify and categorize objects or patterns within images based on predefined criteria or learned models. These basic operations form the foundation of much of the work in image processing, and their successful application can lead to a wide range of practical applications in fields such as medical imaging, remote sensing, and computer vision.

Image processing has found widespread applications across a diverse range of fields, including medicine, remote sensing, biometrics, robotics, digital entertainment, and quality control. In the field of medical imaging, image processing is used for diagnosis, treatment planning, and image-guided interventions in fields such as radiology, pathology, and dermatology. Remote sensing applications involve the analysis of satellite or aerial images for environmental monitoring, land use classification, and disaster management. biometrics is another field where image processing is widely employed, with applications in face recognition, fingerprint identification, and iris scanning for security and authentication purposes. In robotics and automation, image processing is used for visual perception, object detection, and navigation for autonomous vehicles and robotic systems. In the digital entertainment industry, image processing is employed for image editing, special effects, and computer-generated imagery (CGI) in movies, video games, and virtual reality applications. Finally, image processing is also used for quality control and inspection applications such as defect detection, measurement, and sorting in manufacturing and industrial processes. Overall, the broad range of applications for image processing continues to expand and evolve, with new technologies and techniques constantly being developed. The field of image processing promises to play an increasingly important role in shaping our future, both through its practical applications and its theoretical underpinnings.

Despite its many applications and potential benefits, image processing is not without its challenges. These include the management of noisy or low-quality images, the handling of large-scale datasets, and the development of robust algorithms capable of handling real-world applications. In order to overcome these challenges, new techniques are being developed and implemented, including the integration of machine learning and artificial intelligence for automated feature extraction, object recognition, and decision-making in complex visual tasks. Looking toward the future, image processing will continue to play a critical role in analyzing and interpreting digital images for a wide range of applications, contributing to advancements in science, technology, healthcare, and entertainment. However, continued development and innovation will be necessary in order to address new challenges and unlock new possibilities in the digital era. Through ongoing research and collaboration, the field of image processing is poised to make significant contributions to our understanding of the world around us and to the development of new technologies and applications that will shape our future.

1.2 Multispectral Imaging

Multispectral imaging is an advanced imaging technique that involves capturing and analyzing images at multiple discrete wavelengths or spectral bands across the electromagnetic spectrum. Unlike conventional color imaging, which typically captures images in three spectral bands corresponding to the red, green, and blue channels, multispectral imaging captures images in multiple narrow or broad spectral bands, allowing for the acquisition of more detailed and specific information about the objects or scenes being imaged.

The basic principle of multispectral imaging involves using specialized imaging sensors or cameras capable of detecting radiation at different wavelengths, ranging from ultraviolet (UV) and visible light to near-infrared (NIR) and beyond. By capturing images at multiple spectral bands, multispectral imaging can reveal additional information about the composition, structure, and properties of materials that may not be visible to the human eye or captured by conventional imaging techniques. Multispectral imaging involves the acquisition of images at specific discrete wavelengths or wavelength bands across the electromagnetic spectrum. On the other hand, hyperspectral imaging captures images with a much finer spectral resolution, where narrow spectral bands cover a continuous range of wavelengths. Although hyperspectral imaging provides more detailed spectral information, multispectral imaging is often preferred due to its cost-effectiveness and ease of implementation in various applications.

The principles underlying multispectral imaging involve illuminating a sample with light that spans across multiple predetermined wavelength bands. Subsequently, the light interacting with the sample is collected and analyzed using detectors to obtain spectral data. By correlating the intensity of light at different wavelengths with the sample's properties, such as chemical composition, molecular structure, or physical characteristics, useful information about the sample can be extracted. This approach holds significant potential in various fields, including biomedical imaging, environmental monitoring, and material science.

Multispectral imaging has been applied in various fields to gain valuable insights and information. In the field of biomedical imaging, this technique finds its application in disease diagnosis, tissue characterization, and monitoring of therapeutic responses by visualizing specific molecular markers or tissue properties. In the food industry, multispectral imaging can assess food quality attributes such as ripeness, freshness, and contamination by analyzing spectral signatures associated with chemical composition and physical properties. Moreover, agriculture and environmental monitoring benefit from this technique by enabling the assessment of crop health, nutrient content, and environmental factors through the spectral reflectance properties of plants and soil. Lastly, in materials science, multispectral spectroscopic imaging is utilized for material characterization, defect detection, and monitoring of chemical processes in manufacturing.

1.3 Data Analysis and Interpretation:

In multispectral imaging, data analysis and interpretation involve a series of preprocessing steps to ensure the reliability and accuracy of the data. These steps typically include spectral calibration, noise reduction, and image registration to correct for variations and artifacts. Subsequently, chemometric techniques such as principal component analysis (PCA), linear discriminant analysis (LDA), or partial least squares regression (PLS) are commonly used for data analysis and interpretation. These methods enable the extraction of relevant information from the spectral data and the creation of spatial distribution maps of chemical or physical properties. These techniques have proven useful in various applications, such as disease diagnosis, food quality assessment, and materials science

Advantages and Limitations:

Multispectral imaging has proven to be a useful analytical technique, offering several advantages such as spatially resolved spectral information, non-destructive analysis, and versatility for various applications. Nonetheless, this technique also poses several challenges that need to be addressed for accurate and reliable analysis. These challenges include dealing with data complexity, spectral overlap, and instrument calibration requirements. Despite these challenges, multispectral imaging remains a valuable technique in scientific and industrial domains, providing insights into the composition, structure, and properties of materials with spectral specificity and spatial context. Its continued development and integration with advanced data analysis methods hold significant promise for further advancements in research, diagnostics, and quality control applications.

1.4 Egg quality check techniques

1.4.1 Non-destructive Analysis:

Spectroscopic techniques, particularly near-infrared (NIR) spectroscopy and hyperspectral imaging, have emerged as promising tools for non-destructive analysis of eggs. The conventional methods of quality assessment involve breaking or damaging eggs, which compromises their quality and renders them unsuitable for certain applications such as food processing or sale. The non-destructive nature of spectroscopic techniques, on the other hand, enables accurate quality assessment of eggs without compromising their integrity, thereby preserving their quality for subsequent. Therefore, these techniques hold great potential for improving the quality and usability of eggs in various industrial and commercial applications.

Rapid Analysis:

The application of spectroscopic techniques has paved the way for swift analysis of egg quality parameters. By collecting spectral data from eggs and employing chemometric models, it's feasible to obtain real-time feedback on diverse quality attributes, including freshness, nutritional content, and safety. The quick analysis offered by these techniques is especially advantageous in industrial settings, where the processing of large quantities of eggs necessitates efficient and timely assessment of their quality. As such, spectroscopic techniques hold great potential for enabling accelerated and reliable evaluation of eggs in various industrial applications.

Objective and Quantitative Assessment

Spectroscopic techniques have emerged as a reliable means of objectively and quantitatively assessing egg quality parameters. The traditional methods of egg quality assessment often entail subjective visual inspection or manual measurements, which are prone to inter- and intra-observer variability, leading to inconsistency in results. In contrast, spectroscopic techniques generate numerical data by analyzing the interaction of light with the constituents of eggs, facilitating more precise and reproducible measurements. Thus, spectroscopic techniques hold great promise in providing a more reliable and standardized assessment of egg quality, which can have implications for various industrial and commercial applications.

3. Multi-parameter Analysis:

Spectroscopic techniques offer the advantage of simultaneous analysis of multiple quality parameters in eggs. For instance, NIR spectroscopy has been employed to evaluate diverse attributes, including moisture content, protein content, fat content, and cholesterol content in eggs. This multi-parameter analysis provides a holistic understanding of egg quality, enabling more informed decision-making in quality control and assurance processes. The comprehensive analysis offered by spectroscopic techniques has significant implications for various industrial and commercial applications, including food processing, where the quality of eggs plays a critical role in the final product's quality.

4. Versatility and Adaptability:

Spectroscopic techniques offer versatility and adaptability to different egg types, sizes, and production methods. These techniques can be customized to meet specific requirements and variations in egg composition, irrespective of whether the eggs are from chicken, duck, quail, or other avian species. Moreover, the integration of spectroscopic techniques into existing production lines or quality control systems requires minimal modifications, making them practical and widely applicable. The adaptability and versatility of spectroscopic techniques have significant implications for various industrial and commercial applications, including the egg processing industry, where the standardization of quality assessment is crucial to ensure consistent and high-quality products.

5. Cost-effectiveness:

The cost-effectiveness of spectroscopic techniques for egg quality assessment must be considered in light of the higher initial setup costs of spectroscopic equipment and software compared to traditional methods. However, the long-term value of spectroscopic techniques is evident in the streamlining of quality control processes, reduction in waste, and decreased reliance on manual labor. These factors contribute to the overall cost savings for egg producers and processors, making spectroscopic techniques an economically viable option for the egg industry. The adoption of spectroscopic techniques can lead to improved efficiency, accuracy, and consistency in egg quality assessment, which can positively impact various industrial and commercial applications.

1.5 Egg quality check using multispectral over hyperspectral

1. Simplified Data Processing:

Multispectral spectroscopic methods acquire images at a reduced number of predetermined wavelength bands as compared to hyperspectral techniques. Consequently, the data processing and analysis of multispectral data sets are much simpler. Due to the lower number of spectral bands to be handled, multispectral data sets are more manageable and easier to analyze, thereby making them more accessible to novice users with limited expertise in spectral analysis.

2. Reduced Equipment Costs:

Multispectral imaging systems are generally less intricate and costly than their hyperspectral counterparts, as they necessitate fewer optical components and sensors. This results in reduced equipment costs and lower maintenance expenses. As a result, multispectral spectroscopic techniques are more affordable for small-scale egg producers or processors with limited financial resources, thereby enhancing accessibility to these techniques.

3. Faster Data Acquisition:

In the context of high-throughput egg processing facilities, it has been observed that multispectral imaging systems have the potential to facilitate faster data acquisition as compared to hyperspectral systems, primarily owing to their relatively lower spectral resolution. This expedited data acquisition speed can be instrumental in ensuring efficient quality checks and meeting consumer demand in a timely manner, thereby enhancing overall production efficiency.

4. Targeted Analysis:

The utilization of multispectral spectroscopic methods has enabled the focused analysis of distinct quality parameters pertinent to the production and processing of eggs. Through the deliberate selection of wavelength bands that align with significant quality indicators such as nutritional value, freshness, and shell integrity, multispectral imaging has the potential to furnish valuable and actionable information that can enhance product quality and streamline production processes.

5. Enhanced Robustness:

The concept of enhanced robustness can be examined in the context of multispectral imaging systems vis-à-vis their hyperspectral counterparts. The former may possess a higher degree of robustness and reliability, especially when operating in challenging environments. This may be attributed to the limited number of spectral bands and optical components, which renders multispectral systems less prone to issues such as calibration drift, spectral artifacts, or signal noise. Consequently, multispectral systems may offer more consistent and reliable performance over an extended duration of time.

6. Lower Computational Requirements:

According to research, the computational requirements for multispectral data sets are comparatively lower than those for hyperspectral data sets. This is attributed to the fact that multispectral imaging involves processing fewer spectral bands, which in turn, facilitates the use of simpler algorithms and techniques. Consequently, the computational burden is reduced, and it allows for near-real-time quality assessment of eggs.

1.6 Background of a research project

Accurate egg quality detection is important for multiple reasons. From an economic perspective, it helps to minimize food waste by identifying eggs that are not fit for consumption before they reach the market. By doing so, it reduces the cost of production and increases the profit margin for egg producers. From a food safety perspective, accurate egg quality detection helps to identify eggs that may be contaminated with Salmonella or other pathogens that can cause foodborne illnesses. This ensures that only safe and healthy eggs are sold to consumers, reducing the risk of food poisoning.

Conventional inspection methods for egg quality detection are often slow, subjective, and wasteful. They rely on human inspectors, who may have different standards and interpretations of what constitutes a good egg. This can lead to inconsistencies in the quality of eggs that are sold to consumers, and it can also result in unnecessary waste of perfectly good eggs that may not meet the subjective standards of the inspectors.

Sensors such as cameras and microphones offer a more objective and efficient method for egg quality detection. These sensors can examine eggs and assess their quality based on factors such as shell integrity, air cell size, yolk color, and sound. Machine learning algorithms can then analyze this data and categorize the eggs as good, bad, or intermediate, based on pre-defined criteria.

Automated egg quality detection promises to minimize food waste, reduce foodborne illnesses, and ensure consumer satisfaction. It offers a more objective and efficient method for egg quality detection, which can help to increase the profit margin for egg producers, reduce the risk of food poisoning, and ensure that consumers receive high-quality and safe eggs.

1.7 Aim and Objectives

Developing a multispectral setup for egg data acquisition aimed at predicting egg quality involves a meticulous process integrating optical engineering, image processing, and machine learning techniques. The foundation lies in selecting appropriate light sources emitting diverse wavelengths across the electromagnetic spectrum. These sources, including LEDs or halogen lamps, are strategically placed to uniformly illuminate the eggs. Spectral filters are meticulously chosen to isolate specific wavelength bands for each light source, ensuring targeted analysis of various spectral regions. The eggs, positioned uniformly within the imaging area, undergo image capture from multiple angles, enabling comprehensive surface analysis. Calibration of the setup is paramount to ensure consistent measurements, involving standardization of illumination, camera settings, and spectral response. Post-acquisition, images undergo rigorous processing to rectify artifacts and enhance data quality. Advanced algorithms are then employed to extract pertinent features indicative of egg quality, such as color intensity, texture, and spectral signatures. Through machine learning classification techniques, trained models discern patterns within these features to predict egg quality—categorizing eggs as "good" or "bad." Validation of the model's performance is crucial, employing cross-validation methodologies to assess its robustness. The optimized setup, seamlessly integrated into egg processing facilities, facilitates real-time quality assessment and sorting, enhancing efficiency and ensuring product quality standards are met consistently. This iterative process, coupled with ongoing refinement informed by user feedback, perpetuates continuous improvement and adaptation to evolving industry requirements.

1.8 Hypothesis

Applying a multispectral imaging system to evaluate egg quality will provide a more accurate, non-destructive, and comprehensive analysis compared to traditional methods. By capturing images at multiple wavelengths, the system can detect subtle differences in eggshell and content quality, leading to improved classification and grading of eggs based on parameters such as shell integrity, yolk quality, and potential internal defects."

This hypothesis posits that the multispectral approach enhances the precision and reliability of egg quality assessment

CHAPTER-2

L I T E R A T U R E R E V I E W

2. Literature Review

The study of Anca Galiş et. al, [1] has explored the potential of using near-infrared (NIR) spectroscopy for assessing the quality of eggs and egg products. The findings indicated that NIR spectroscopy is a reliable, non-destructive, and fast method for evaluating several quality attributes, including freshness, nutritional composition, and functional properties. The accuracy of the method in predicting various parameters, such as egg freshness, protein content, fat content, and egg yolk color, was also noteworthy. The results suggest that NIR spectroscopy can be an effective quality control tool for the egg industry, providing benefits such as speed, efficiency, and cost-effectiveness compared to traditional methods. Nonetheless, it is essential to conduct additional research to optimize and validate NIR spectroscopy techniques for different types of egg products and processing conditions.

The aim of Ketelaere, B. D.et. al,[2] is study was to determine the feasibility of using near-infrared (NIR) spectroscopy to measure egg quality non-destructively. The results showed that NIR spectroscopy accurately assessed various quality parameters of eggs, including freshness, nutritional composition, and functional properties, without causing any damage to the egg. The study concluded that NIR spectroscopy is a reliable, rapid, and cost-effective method for evaluating egg quality, and it offers advantages over traditional destructive methods. These findings suggest that NIR spectroscopy has great potential as a tool for quality control in the egg industry, providing a non-invasive and efficient means of monitoring egg quality throughout the production and distribution process. Nevertheless, further research is necessary to optimize and validate NIR spectroscopy techniques for different types of eggs and processing conditions to ensure their practical application in the industry.

The objective of Hüseyin Güray Çiftç et. al,[3] study was to evaluate the effectiveness of chemometric methods in monitoring quality changes and freshness assessment of eggs using near-infrared (NIR) spectroscopy. The results indicated that chemometric analysis, in combination with NIR spectroscopy, can efficiently evaluate the freshness and quality changes of eggs during storage. The study developed various chemometric models that correlated NIR spectra with quality parameters, such as freshness, egg weight, yolk color, albumen height, and Haugh unit. These models demonstrated high accuracy in predicting the freshness and quality attributes of eggs. The study concluded that chemometric methods, particularly when combined with NIR spectroscopy, offer a reliable, non-destructive, and fast approach for monitoring egg quality and freshness, providing valuable tools for the egg industry to ensure product quality and safety.

A recent study of Akowuah, T. O. S , [4] has presented a new technique for determining egg freshness and the marked date of lay that is both rapid and non-destructive. This method uses spectral fingerprinting to examine the spectral fingerprints of eggshells, which allows the researchers to classify eggs into different freshness categories and determine the date of lay with good accuracy. This method shows great promise for the egg industry, as it provides a fast and efficient way to assess egg freshness without causing any damage to the eggs. Furthermore, this technique could help reduce food waste by ensuring that eggs are used before they spoil, ultimately benefiting both producers and consumers.

A recent study of Kim, J., Semyalo, D. et. al,[5] has introduced a non-destructive method for detecting abnormal chicken eggs using an optimized spectral analysis system. The approach involves analyzing the spectral characteristics of eggs to accurately identify abnormal eggs without damaging them. The study showed that the system has high sensitivity and specificity in detecting various types of abnormalities in eggs, such as hairline cracks, blood spots, and meat spots. This method offers a rapid and efficient way to sort out abnormal eggs in the production line, helping to ensure the quality and safety of chicken eggs for consumers. Furthermore, this technique could potentially reduce economic losses for egg producers and improve overall egg quality control in the poultry industry.

A recent review paper of Qi, L., Zhao, M., Li, Z. et. al, [6]has explored non-destructive testing technology for evaluating the freshness of raw eggs. The paper provides an overview of various methods and technologies used for determining egg freshness without causing any damage to the eggs. These methods include spectroscopy, computer vision, electronic nose, and ultrasonic techniques, among others. The review highlights the advantages and limitations of each method and discusses their potential applications in the egg industry. By using non-destructive testing technology, producers can quickly and accurately assess the freshness of raw eggs, helping to reduce food waste and ensure product quality for consumers. Furthermore, this approach could potentially improve the overall efficiency and profitability of the egg industry by reducing the need for destructive testing methods.

The recent study of Yao, K., Sun, J. et. al,[7] introduces a non-destructive method for detecting S-ovalbumin content in eggs, utilizing a portable near-infrared (NIR) spectrometer and multiphoton absorption coherent anti-Stokes Raman scattering (MPA-CARS) spectroscopy. The researchers aimed to accurately quantify the amount of S-ovalbumin without damaging the eggs by analyzing the spectral characteristics of the eggs, particularly focusing on S-ovalbumin content. The combination of NIR spectrometer and MPA-CARS spectroscopy showed high sensitivity and specificity in detecting S-ovalbumin, even at very low concentrations. This method could be of significant importance for assessing the quality and safety of eggs, particularly in terms of allergen detection, providing valuable information for consumers with egg allergies. Additionally, it has the potential to improve quality control measures in the egg industry, ensuring that eggs meet regulatory standards and consumer expectations.

In Juntae Kim et. al,[8] It's fascinating to see how spectrometers are being used to detect abnormal eggs in real-time. It's fascinating to see how spectrometers are being used to detect abnormal eggs in real-time. The study focused on optimizing the parameters for detecting internal egg abnormalities using visible and near-infrared (Vis/NIR) spectrometry and multivariate data analysis. They looked into various system parameters such as light source types, light configuration, and sensor positions to improve detection performance. The study successfully developed a model that achieved a high classification accuracy of 98.7% using partial least-squares discriminant analysis (PLS-DA). They also used different band selection methods to optimize the model and reduce spectral-bands to less than 7. This research really highlights the importance of system optimization in egg quality assessment.

The paper of Wang Qiaohua et. al,[9] lacks detailed information on the mathematical models used for calculating the initial mass and volume of the egg, which might make it challenging for other researchers to understand the methodology. Additionally, it doesn't provide specifics about the weighing sensor technology used for measuring the current egg weight, which could affect the accuracy and precision of the measurements. Furthermore, the paper doesn't discuss the potential challenges or limitations encountered during the development or implementation of the rapid nondestructive detection system, which could offer valuable insights into the practical feasibility and real-world applicability of the proposed method. Finally, there is no mention of the potential impact of environmental factors or variations in egg characteristics on the accuracy of the freshness detection method, which could affect the applicability of the findings to different scenarios.

The paper Rong Weiyi et. al, [10] primarily focuses on the development and description of the egg online nondestructive detection system, but it lacks detailed information on certain aspects. It does not extensively discuss the specific technical specifications of the detection module, such as the sensitivity levels or the range of crack detection capabilities. Additionally, it does not provide information on the potential challenges or limitations faced during the implementation or testing phases of the system. Furthermore, the scalability of the system is not clearly addressed. It is unclear whether the system can be easily scaled up for industrial-level egg processing or if there are any limitations in doing so. The paper also does not mention any comparative analysis with existing egg detection systems, making it difficult to assess the novelty and effectiveness of the proposed system in comparison to other similar technologies in the market. Finally, the paper does not discuss the cost implications of implementing the online nondestructive detection system, which is crucial information for practical implementation in real-world scenarios.

The paper Duan Xiang et. al, [11] introduces a non-destructive method for assessing egg freshness through centroid measurement, offering a rapid and cost-effective approach. Unlike traditional destructive techniques, this method provides an innovative and practical solution for egg freshness detection. It involves real-time measurement of the distance between the centroid of an egg and the top of the small end, defining a centroid ratio that correlates with the egg's freshness. The models established based on the centroid ratio effectively predict the number of days an egg has been stored and its freshness degree. This method is highlighted for its efficiency and cost-effectiveness, making it suitable for industries involved in egg production and distribution. Furthermore, by analyzing the change rule and influence factors on egg freshness over the storage period, this method offers valuable insights for maintaining egg quality and safety in the supply chain

The research paper Xu Yedong et. al, [12] discusses an egg detection method centered around a detection and sorting device for distinguishing egg quality. The method involves several steps, including initiating rotating disks, utilizing an X-ray machine for irradiation, transporting qualified eggs to a packaging area, and sorting them based on sizes using a sorter. X-ray technology is commonly used in the food industry for non-destructive testing of eggs, enabling the detection of defects without compromising the egg's integrity. Sorting eggs based on size is essential for packaging and distribution, as uniform size ensures consistency in cooking and presentation. The automation of egg processing, including the use of sorting devices and rotating disks, contributes to streamlining the production line, enhancing efficiency, and reducing manual labor costs. The integration of detection and sorting devices in the egg processing industry reflects a move towards more advanced and precise quality control measures.

The paper Md. Hamidul Islam et. al, [13] introduces a new nondestructive method for detecting egg quality based on the unit weight of an egg, falling within the technical domain of nondestructive detection of agricultural products. This method involves the rapid processing of egg images, establishing linear relationships between egg area, volume, and unit weight, calculating the unit weight of each egg, and correlating the unit weight with the Haugh unit to predict egg freshness. The Haugh unit serves as a common index for egg freshness, categorizing eggs based on their unit weight (rho) into highly fresh and suitable for consumption, edible, poor freshness and not recommended for consumption, and not fit for consumption. This method enables the swift and straightforward assessment of egg freshness by inputting egg images into a system, streamlining the grading process for eggs based on their quality.

The research paper Li Xingmin et. al, [14] presents an innovative non-destructive method for detecting egg freshness using an electromagnetic wave resonant cavity. Previous studies have explored a range of techniques for assessing egg quality, including traditional methods such as candling, as well as newer technologies like spectroscopy and computer vision. Some research has delved into the use of electronic noses or gas sensors to detect volatile compounds associated with egg freshness, while others have investigated impedance spectroscopy or electrical conductivity measurements for assessing egg quality. Additionally, research in the field of food quality control has looked into the application of machine learning algorithms for predicting egg freshness based on various parameters. Collectively, the literature indicates a growing interest in developing non-invasive and accurate methods for evaluating egg freshness to meet consumer demands for quality assurance in food products

In Lei-ming Yuan et. al, [15] Egg freshness plays a vital role in daily nutrition and food consumption. Factors such as temperature, storage time, humidity, and airflow velocity have a significant impact on egg quality. In the methodology, the research utilized Vis-NIR spectroscopy combined with iPLS for non-destructive egg freshness measurement. Semi-transmittance spectral acquisition was employed within a spectral range of 550-985 nm. The Haugh Unit (HU), ranging from 56-91 in 14 days post-delivery, served as a key freshness indicator. iPLS models were developed based on spectral intervals to predict

HU, with Lasso used for model selection and fusion regression. The experimental setup involved storing eggs in a constant incubator, with storage time as the controlling factor. The study specifically focused on assessing the impact of storage time on egg freshness, incorporating varying spectral intervals for model development.

The paper Loffredi, E., Grassi, S. et. al, [16], explores the potential of spectroscopic techniques for non-destructive evaluation of shell egg quality and freshness, highlighting both opportunities and challenges. Spectroscopic methods, including visible and near-infrared spectroscopy, Raman spectroscopy, and hyperspectral imaging, offer promising avenues for assessing egg quality parameters such as shell thickness, shell strength, yolk color, and freshness without damaging the eggs. These techniques provide rapid, non-destructive, and accurate measurements, enabling early detection of egg spoilage and reducing economic losses. However, challenges such as sample variability, instrument calibration, and data analysis complexity need to be addressed for successful implementation of spectroscopic approaches in the egg industry. Despite these challenges, the paper underscores the significant potential of spectroscopic methods for enhancing egg quality and freshness evaluation.

The paperLin, H., Zhao, J. et. al [17], investigates the feasibility of using near-infrared (NIR) spectroscopy combined with multivariate data analysis for the non-destructive measurement of egg freshness. NIR spectroscopy has emerged as a promising technique for assessing food quality parameters due to its rapid and non-destructive nature. By analyzing the spectral data collected from egg samples, multivariate data analysis techniques such as principal component analysis (PCA) and partial least squares regression (PLSR) are employed to develop predictive models for egg freshness. The results demonstrate that NIR spectroscopy combined with appropriate multivariate data analysis techniques can accurately predict the freshness of eggs, offering a fast and non-destructive method for quality control in the egg industry.

The paper Ketelaere, B. D. et. al, [18], explores non-destructive methods for assessing egg quality, aiming to develop efficient techniques for quality control in the egg industry. Various spectroscopic techniques such as near-infrared spectroscopy (NIR), Raman spectroscopy, and hyperspectral imaging are investigated for their potential in measuring egg quality parameters such as shell thickness, shell strength, yolk color, and freshness. These non-destructive methods offer advantages over traditional destructive techniques by providing rapid and accurate measurements without damaging the eggs. However, challenges such as sample variability, instrument calibration, and data analysis complexity need to be addressed for successful implementation of non-destructive techniques in the egg industry. Despite these challenges, the paper concludes that spectroscopic approaches hold significant promise for enhancing egg quality assessment, enabling early detection of egg spoilage, and reducing economic losses in the egg production process.

The paper Dai, D., Jiang. Et. al,[19], investigates a non-destructive method for detecting egg freshness based on hyperspectral scattering imaging combined with ensemble learning techniques. By analyzing the hyperspectral scattering images of eggshells, an ensemble learning model is developed to predict egg freshness. The model combines multiple base classifiers to improve prediction accuracy. Experimental results demonstrate that the proposed method achieves high accuracy in detecting egg freshness, outperforming traditional methods. The non-destructive nature of hyperspectral scattering imaging makes it a promising technique for quality control in the egg industry, offering a rapid and reliable way to assess egg freshness without damaging the eggs.

The study , et. al,aimed to compare egg quality characteristics across poultry species using digital image analysis and conventional methods. It found a strong correlation between the two approaches for parameters such as egg length, width, and shape index. The study emphasized the importance of proper calibration and reference points in digital image analysis for accurate determination of egg quality characteristics.

CHAPTER - 3

D A T A B A S E

3. Database

1.Database Acquisition Set-Up

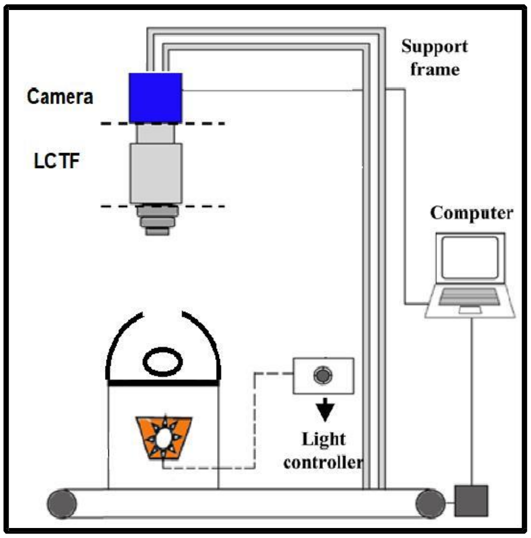


Figure 1 Diagrammatic Database Acquisition Set-Up

Figure 2 Database Acquisition Set-Up

The experimental setup was meticulously designed and implemented in a controlled environment within a dark room to ensure accurate data acquisition and analysis. The wooden box housing the light sources was lined with aluminum foil on its inner walls to create a uniformly illuminated system, minimizing reflections and ensuring consistent lighting conditions. A circular opening was positioned on the top side of the box, covered with glass and equipped with provisions for mounting the eggs at the center of the glass. To achieve uniform illumination on the sample, a dome with a diameter matching the circular opening of the box was placed atop the glass. This dome served to evenly distribute light across the surface of the eggs, ensuring consistent illumination for each measurement.

Figure 3 image of illuminating box set up

Two distinct light sources were utilized in the experiment: an incandescent light bulb and a xenon light source. Both light sources offered broad spectral coverage, enabling the exploration of a wide range of wavelengths from 400 nanometers to 720 nanometers. Spectral wavelengths were varied systematically in increments of 20 nanometers, allowing for detailed spectral analysis of the eggs' optical properties under different illumination conditions.

The experimental procedure involved focusing the detector on the egg through the opening of the dome, capturing the light transmitted through the egg, and saving the output as images. This process was repeated for each wavelength increment across the spectrum, resulting in a comprehensive dataset of spectral images for analysis.

Figure 4 Sample Placement

The overarching aim of the experimental design was to obtain robust and meaningful data that could be subjected to statistical analysis. By systematically varying the spectral wavelengths and utilizing two different light sources, the study sought to explore the spectral characteristics of the eggs and investigate potential differences in their optical properties under different lighting conditions. The comprehensive dataset generated through this experimental approach provided a solid foundation for statistical analysis, enabling the derivation of meaningful conclusions regarding the spectral signatures of the eggs and their potential implications for quality assessment and classification

Figure 5 Practical Setup

3.1 Incandescent light bulbs

Incandescent light bulbs emit light through the process of thermal radiation, wherein a heated filament inside the bulb generates light across a broad spectrum of wavelengths. This spectrum encompasses not only visible light but also extends into the infrared region, making it suitable for a variety of lighting applications. Within the visible light range, the emitted wavelengths typically span from approximately 400 nanometers to around 700 nanometers, covering the entire visible spectrum from violet to red light. Unlike certain other light sources such as fluorescent or LED bulbs, which emit light in more discrete bands or lines, the spectral distribution of incandescent bulbs is relatively continuous. This continuous spectrum results from the thermal excitation of atoms within the filament, leading to the emission of a broad range of wavelengths. While incandescent bulbs have been widely used for their ability to produce warm and natural-looking light, they are less energy-efficient compared to newer lighting technologies and have been gradually replaced in many applications. However, their broad and continuous spectral output remains a characteristic feature, making them suitable for certain specialized applications where a broad spectrum of light is desired, such as in photography or colorimetry.

Figure 6 Incandescent light bulbs

3.2 Xenon light bulbs

Xenon light bulbs represent a departure from the traditional incandescent bulbs in terms of their operating principle and mechanism of light generation. Unlike incandescent bulbs, which rely on a heated filament to produce light through thermal radiation, xenon lamps generate light by exciting xenon gas through an electrical discharge. This process involves applying a high voltage across the xenon-filled bulb, ionizing the gas and creating a plasma arc that emits intense light. One of the significant advantages of xenon lamps is their ability to produce visible light that covers a broad range of wavelengths within the visible spectrum, typically ranging from approximately 400 nanometers to around 700 nanometers. This encompasses the entire spectrum of colors visible to the human eye, from violet to red light, making them well-suited to applications where accurate color rendition is necessary. The emitted light from xenon lamps is characterized by its high intensity and relatively uniform spectral distribution across this range of wavelengths.

Unlike some light sources that emit light in discrete bands or lines, xenon lamps produce a continuous spectrum of light. This continuous spectral output results from the excitation of xenon atoms in the gas discharge, which leads to the emission of photons across a broad range of energies and wavelengths.

Xenon light bulbs are commonly used in various applications where high-intensity, white light is required, such as automotive headlights, movie projectors, and industrial lighting. Their ability to produce intense light with a broad and continuous spectral output makes them well-suited for these applications, where accurate color rendition and high visibility are essential. Additionally, xenon lamps have a longer lifespan and higher efficiency compared to traditional incandescent bulbs, contributing to their widespread adoption in diverse lighting scenarios.

Figure 7 Xenon light bulbs

3.3 The Liquid Crystal Tunable Filter (LCTF)

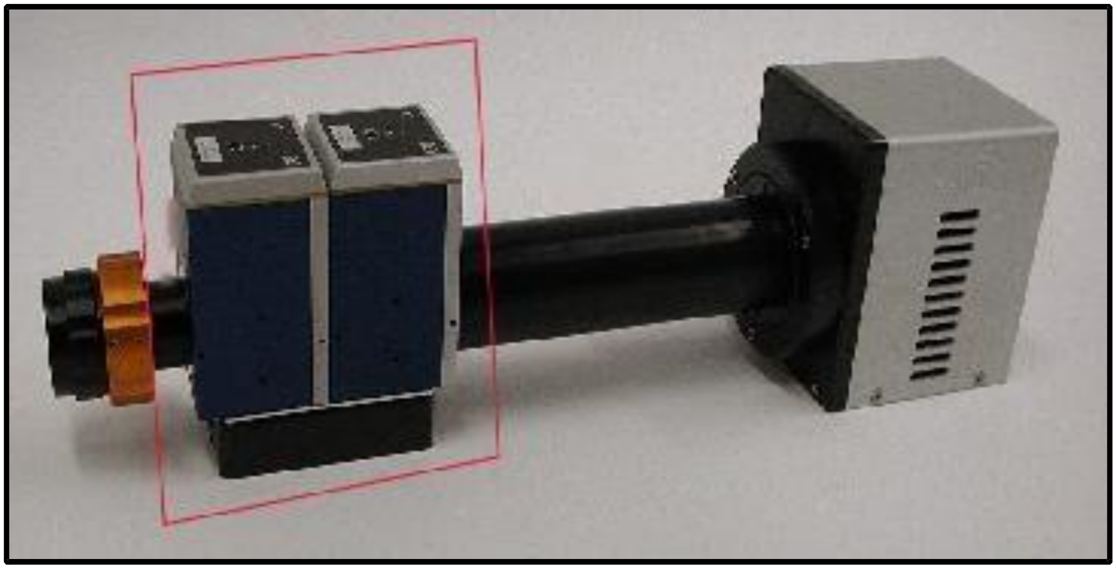


Figure 8 The Liquid Crystal Tunable Filter

The Liquid Crystal Tunable Filter (LCTF) Varispec is a type of optical filter that utilizes liquid crystal technology to selectively transmit light across a range of wavelengths. It offers tunability and flexibility in wavelength selection, making it valuable for various spectroscopic and imaging applications. Here's a detailed explanation of the Liquid Crystal Tunable Filter Varispec

Principle of Operation:

The operational mechanism of the LCTF Varispec is grounded in the phenomenon of birefringence, which is exhibited by liquid crystal materials. These materials possess both liquid and crystalline properties and their optical characteristics can be manipulated by the application of an electric field. The LCTF Varispec features a sandwich-like structure, incorporating two glass plates coated with transparent electrodes and a layer of liquid crystal material positioned between them. Upon the application of an electric field, there is a change in the refractive index of the liquid crystal material, thereby causing a shift in the wavelength of light that can traverse the filter.

Tunability and Flexibility:

The LCTF Varispec presents an essential characteristic of tunability, which is one of its salient features. This attribute is made possible by adjusting the voltage applied to the electrodes, thereby allowing users to control the wavelength of light transmitted through the filter. Such a tunability feature enables the precise selection of specific wavelengths or wavelength ranges, thereby making it well-suited for a wide range of applications. Furthermore, the LCTF Varispec offers remarkable flexibility in wavelength selection. Unlike fixed-bandpass filters or grating-based spectrometers, which are constrained to particular wavelengths or spectral ranges, the LCTF Varispec can be continuously adjusted across a broad spectral range, spanning from ultraviolet (UV) to near-infrared (NIR) wavelengths.

Applications:

The LCTF Varispec has found diverse applications in several fields, including: Spectroscopy: It can be utilized as a tunable bandpass filter in spectrophotometers, fluorescence microscopes, and hyperspectral imaging systems, enabling precise wavelength selection and spectral analysis. Imaging: In microscopy and biomedical imaging, the LCTF Varispec allows for multispectral and hyperspectral imaging, thereby facilitating the acquisition of spatially resolved spectral information from biological samples, tissues, and materials. Remote Sensing: In remote sensing applications, the LCTF Varispec can be employed for hyperspectral imaging of the Earth's surface, vegetation, and atmospheric phenomena, thereby providing valuable data for environmental monitoring, agriculture, and geology. Material Analysis: It is employed in material characterization, quality control, and defect detection processes where precise spectral analysis is required to identify and quantify chemical compounds, pigments, or structural properties of materials.

Advantages:

The LCTF Varispec presents various advantages, including: Tunability: It provides precise control over the transmitted wavelength, thus enabling the selection of specific wavelengths or wavelength ranges. Flexibility: The LCTF Varispec can be continuously tuned across a broad spectral range, making it possible to analyze a wide range of samples. Compact and Lightweight: It is well-suited for integration into compact optical systems, thereby facilitating its use in portable, field-based, or space-constrained applications. High Speed: The LCTF Varispec has rapid tuning capabilities, thereby enabling the real-time acquisition of spectroscopic and imaging data.

Limitations:

The LCTF Varispec also has some limitations, including Limited Resolution: The spectral resolution of the LCTF Varispec may be lower compared to other spectroscopic techniques, thereby limiting its utility in some applications. Polarization Sensitivity: The performance of the LCTF Varispec may be influenced by the polarization state of the incident light, thereby requiring careful attention to polarization characteristics.

Temperature Sensitivity: The operating characteristics of the LCTF Varispec may be affected by changes in temperature, thereby necessitating temperature control or correction procedures.

3.4 BCI5-U-M-40 C-Cam

Figure 9 BCI5-U-M-40 C-Cam

The BCi5 camera is a very compact, high-resolution CMOS camera. The camera is equipped with the Ibis5a image sensor with 6.7 µm square pixels. The user can define any Window Of Interest within a 1280 x 1024 pixel area, also known as the SXGA format. The sensor has a remarkably good signal-to-noise ratio in combination with excellent contrast performance The image sensor has a Multi-Slope Exposure mode that prevents over-exposure of brighter parts of an image while preserving excellent contrast in the darker areas of the image. In this way, the dynamic range is extended from 60 dB up to 100 dB. The BCi5 camera can be switched between normal and Multi-Slope mode. The digital camera operates in single-shot mode, which makes it ideal for machine vision applications. In this mode, the user has the freedom to decide when the camera has to capture an image, not the other way around as is the case with most analog camera systems. Continuous capture mode is also supported. The in-camera memory of 8 Mbytes is used as image FIFO in USB2.0 and IEEE-1394 interfaces and can be used with custom camera logic for other purposes, such as reference images, camera calibration data… C-Cam Technologies supply several standard interfaces: Serial LVDS, USB 2.0, IEEE-1394, or Camera Link. The Camera Link and Serial LVDS interfaces allow for remote triggering via the interface cable. They also have a local trigger input and output. The IEEE-1394 and USB 2.0 versions have local trigger input and output. The BCi5 comes with Drivers and DLL files and sample code in Visual C (Windows 98,Me, 2000, XP, and NT4.0). Software engineers can easily adapt the code to integrate into their own applications. Include files for Visual Basic and Delphi are supplied. The IEEE-1394 version is DCAM 1.3 compliant.

3.5 Data acquisition Protocol

The experimental setup for this study involved the use of two types of light sources, namely incandescent and xenon light bulbs, with a wavelength range of 400nm to 700nm and a broad spectrum. Eggs were placed on a glass surface above the bulb, and light rays were passed through the egg sample. The light rays that passed through the samples were observed using a detector and captured using a BCi5-C-Cam and a liquid crystal tunable filter (LCTF). The LCTF was used to select a specific wavelength of light while blocking all other lights within the range of 400nm to 720nm with an increment of 20nm. A total of 17 wavelengths were taken, and for each wavelength, three images were captured. This procedure was repeated for 30 eggs, resulting in a total of 3060 images in the database. Out of these images, 1530 were captured using the incandescent light bulb, including 918 good egg images and 612 bad egg images. The same was calculated for the xenon bulb. After obtaining the total of 3060 images using both incandescent and xenon bulbs for good and bad eggs, a technique called feature extraction and classification was applied to these images.

Sample	Incandescent light bulb		Xenon	
	Good	Bad	Good	Bad
400	3	3	3	3
420	3	3	3	3
440	3	3	3	3
460	3	3	3	3
480	3	3	3	3
500	3	3	3	3
520	3	3	3	3
540	3	3	3	3
560	3	3	3	3
580	3	3	3	3
600	3	3	3	3
620	3	3	3	3
640	3	3	3	3
660	3	3	3	3
680	3	3	3	3
700	3	3	3	3
720	3	3	3	3
Total samples across spectra's	51	51	51	51
Total Eggs	18	12	18	12
Total Images	918	612	918	612
	1530		1530	

Table 1 Data Acquisition Table for Multispectral Egg Quality Check

3.6 Acquired images

Bad egg data

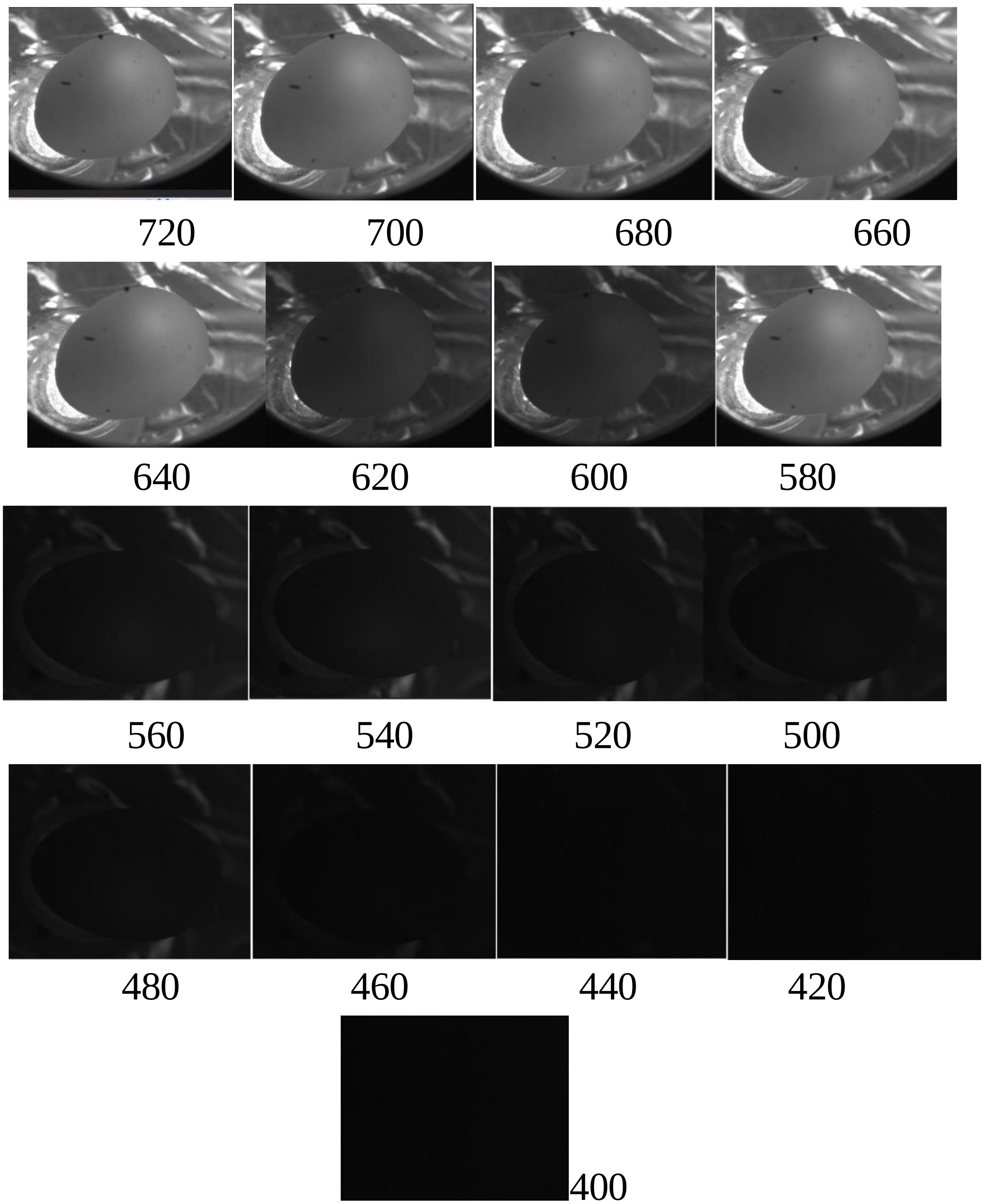


Figure 10 Bad eggs data images using an Incandescent bulb

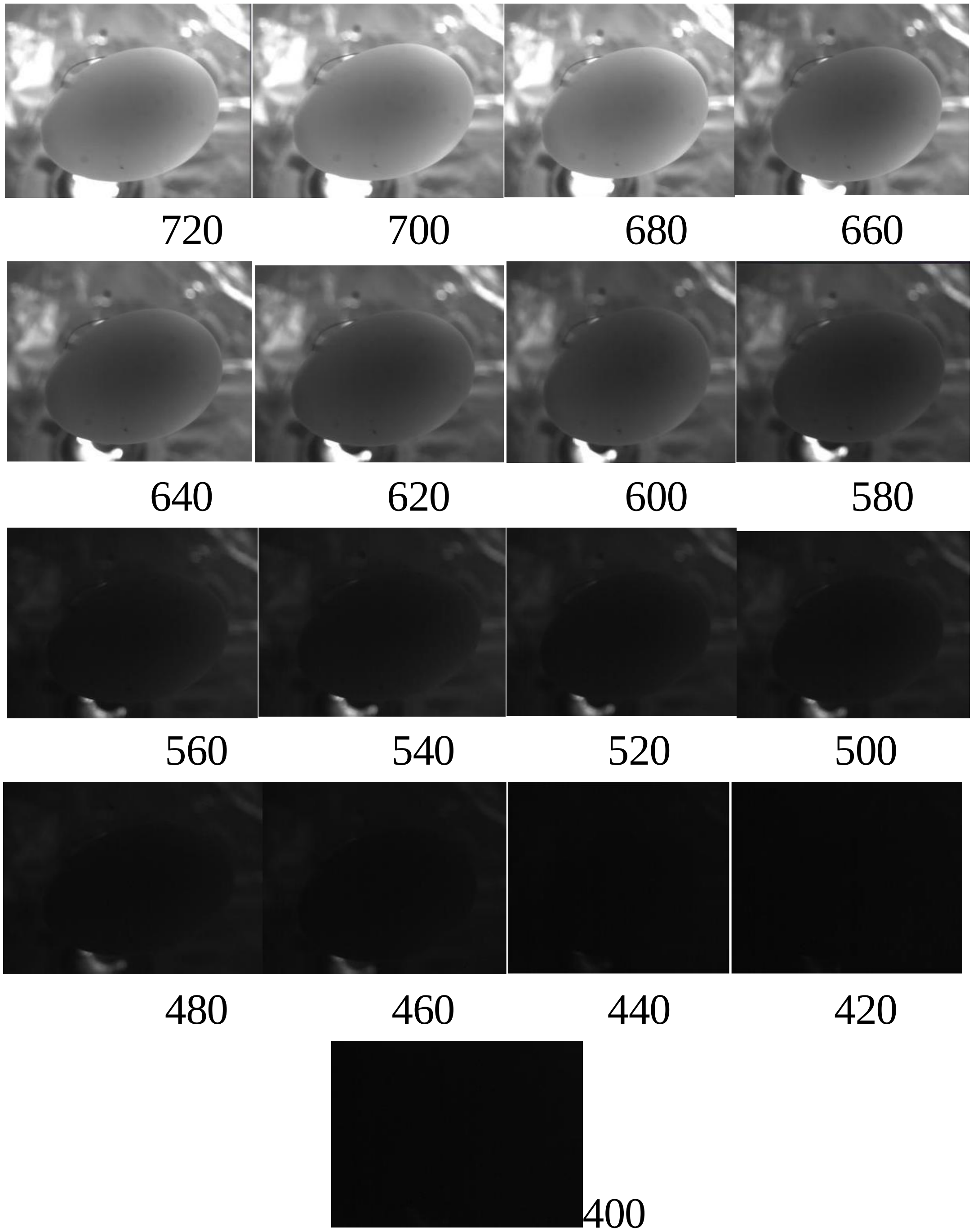
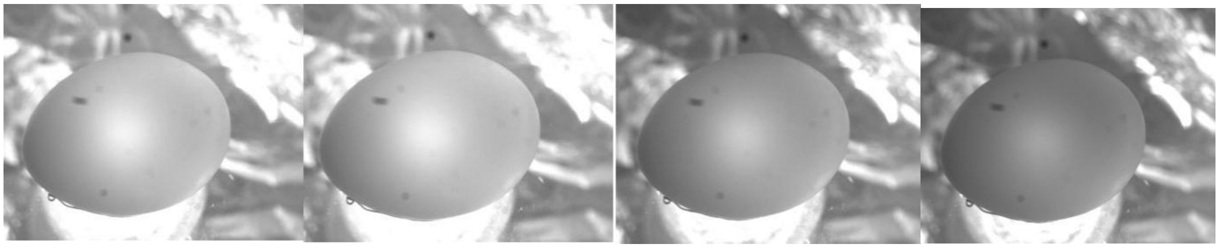
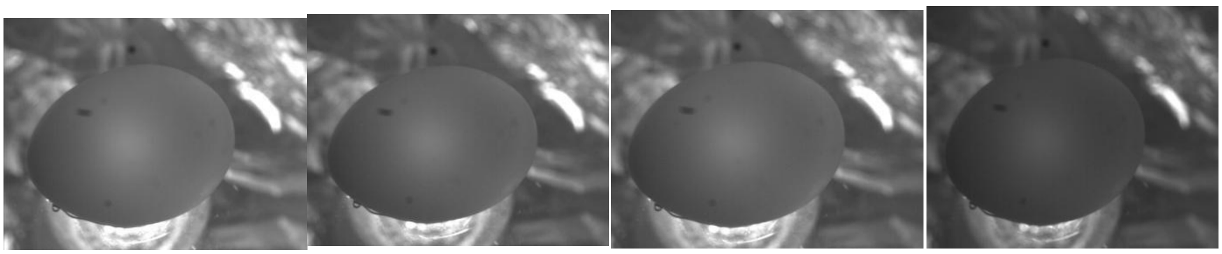


Figure 11 Bad eggs data using xenon light

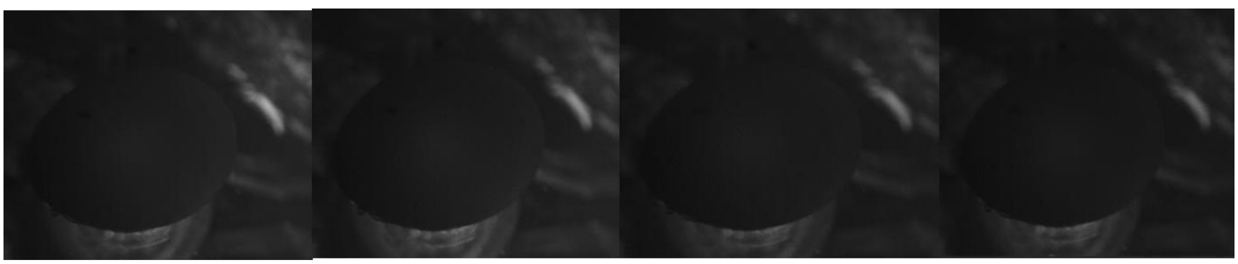
Good eggs data



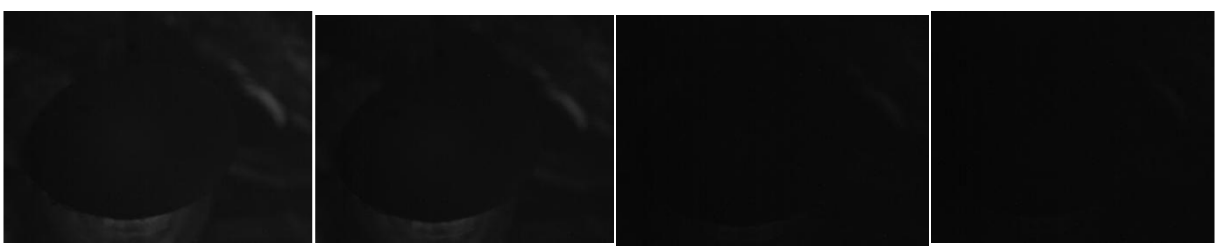
720 700 680 660



640 620 600 580



560 540 520 500

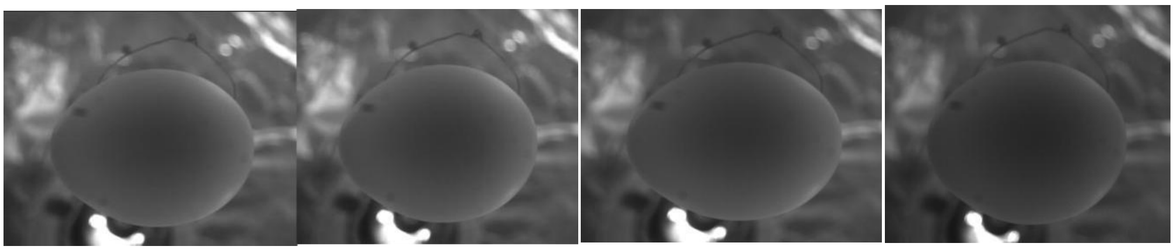


480 460 440 420

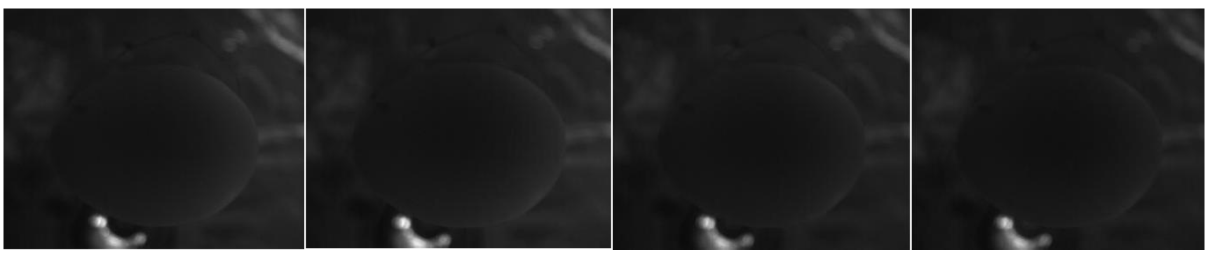
400

Figure 12 Good eggs data images using an incandescent bulb

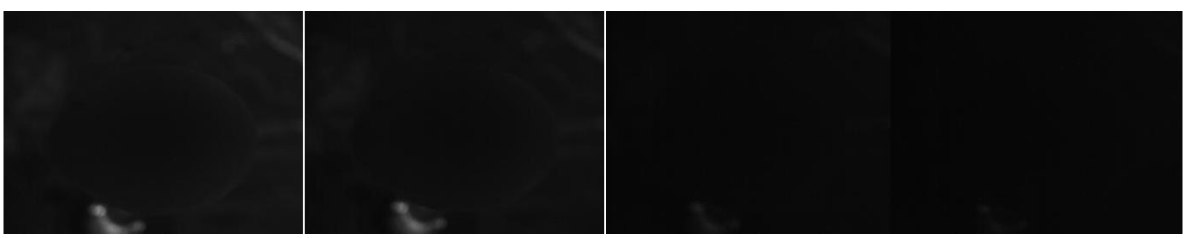
720 700 680 660



640 620 600 580



560 540 520 500



480 460 440 420

400

Figure 13 Good eggs data images using Xenon

CHAPTER - 4

M E T H O D O L O G Y

4. Methodology

4.1 System block (explain)

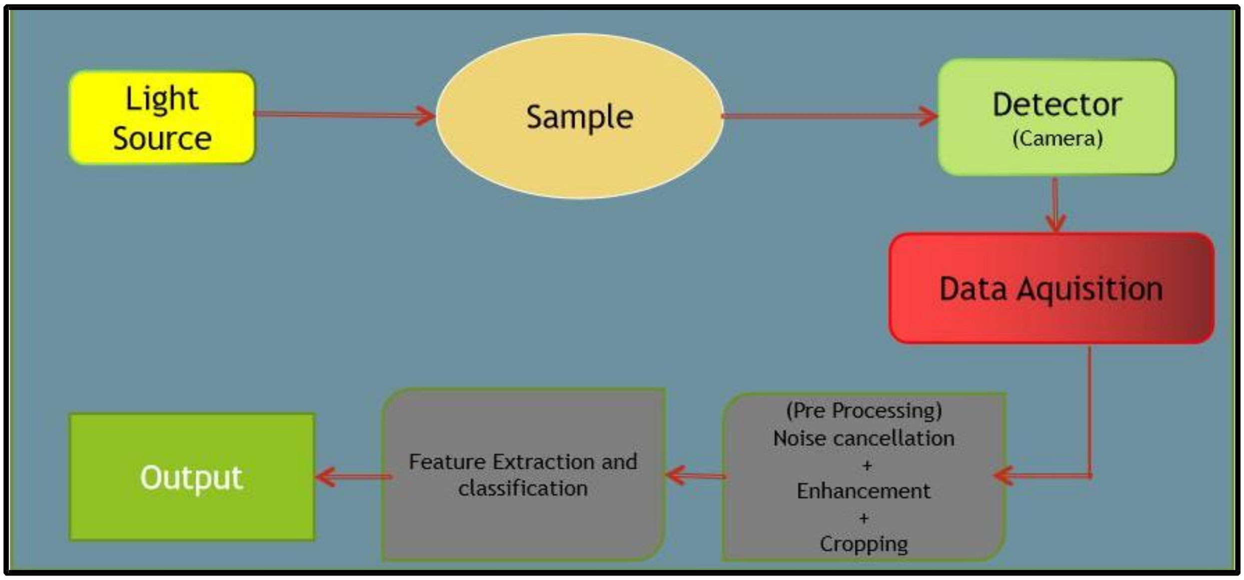


Figure 14 System Block Diagram

From figure 14 The system block diagram for the Multispectral Approach for Egg Quality Check consists of crucial components including the light source, sample, detector, data acquisition, pre-processing, feature extraction and classification, and the output. The light source, such as an Incandescent bulb and xenon bulb, plays a crucial role in illuminating the egg and significantly impacts the quality of the collected data. The detector, responsible for capturing the reflected light from the egg, also plays a crucial role in the quality of the collected data. Following data collection, the data acquisition process serves to enhance the quality of the signal, and the pre-processing stage involves preparing the collected data for analysis. Feature extraction and classification involve identifying and extracting key characteristics from the data, which are then utilized in a classification algorithm to categorize the egg as good or bad. The multispectral approach offers a non-destructive method of evaluating egg quality by leveraging light of varying wavelengths to enable data collection beyond the spectrum of human vision, contributing to enhanced food safety and consumer satisfaction.

4.2 Pre-Processing Techniques

Image adjustment,

Image adjustment is a complex and nuanced process that involves a range of techniques to enhance, refine, or correct digital images to achieve the desired visual outcomes. This process includes a vast array of adjustments that are tailored to improve the quality, appearance, and usability of images in various applications and contexts. The core of image adjustment involves manipulating visual attributes such as brightness and contrast. Adjusting brightness involves fine-tuning the overall luminance levels of an image, while contrast adjustments amplify or moderate the disparities between light and dark regions, enhancing the image's visual depth and impact. In addition, color balance adjustments play a crucial role in ensuring faithful color representation, requiring careful calibration of the red, green, and blue color channels' relative intensities to rectify any color casts or deviations from natural hues.

Saturation adjustments elevate the vibrancy and richness of colors, giving images a more vivid and striking appearance. Sharpness adjustments refine the clarity and detail of edges and textures, giving images a crisp and polished look. Exposure adjustments are also vital in rectifying any inconsistencies in exposure levels, harmonizing tonal distribution and dynamic range to ensure optimal image fidelity and balance. Sophisticated noise reduction techniques are essential to mitigate unwanted noise or graininess, preserving image clarity and integrity, especially in images captured under challenging conditions or with high ISO settings.

White balance adjustments are also crucial in achieving accurate color rendition, compensating for variations in color temperature to achieve neutral whites and consistent color fidelity across diverse lighting conditions. These adjustment techniques may be applied manually using specialized image editing software or automated algorithms integrated into advanced image processing tools.

Overall, the meticulous orchestration of image adjustment techniques is essential in optimizing image quality, catering to various needs and exigencies across numerous disciplines and domains, including photography, graphic design, digital artistry, scientific inquiry, and beyond

Image alignment

One of the significant challenges in image alignment is dealing with images that contain noise or artifacts, as these can significantly affect the accuracy of the alignment process. To address this issue, pre-processing techniques such as noise reduction or artifact removal may be employed to improve the quality of the images before alignment.

Another area of active research in image alignment is the use of machine learning-based approaches. For example, deep neural networks can learn to align images by training on a large dataset of aligned image pairs. These networks can then be used to align new images without the need for explicit feature extraction or parameter tuning, making the alignment process more automatic and efficient.

Furthermore, the choice of reference image or coordinate system can significantly impact the quality of the alignment. In some cases, it may be necessary to select a different reference image or coordinate system to obtain optimal alignment results. Moreover, hybrid methods that combine different alignment techniques can be used to improve the accuracy and robustness of the alignment process.

It's worth noting that image alignment is not only limited to scientific applications but also has significant implications in everyday life. For instance, image alignment is used in smartphone cameras to improve the quality of panoramic images or to reduce motion blur in low-light conditions.

Finally, the importance of image alignment underscores the need for high-quality data in image-based research. The quality of the data used for alignment can significantly affect the accuracy and reliability of the subsequent analysis, and it is essential to ensure that the data are of sufficient quality for the intended purpose.

In conclusion, image alignment is a critical procedure in image processing, with significant implications in various applications. The choice of alignment technique, reference image, and coordinate system can significantly impact the accuracy and robustness of the alignment process. With new advances in machine learning and hybrid alignment techniques, the future of image alignment looks promising, and it is likely to play an even more critical role in unlocking the potential of image data.

Image Enhancement

Image enhancement is a critical aspect of digital image processing, which involves a diverse array of techniques aimed at refining, augmenting, or rectifying the visual quality and interpretability of digital images. This process is critical in various applications, including medical imaging, satellite imaging, surveillance, photography, and digital art, where it serves to elevate image quality, extract meaningful information, and enhance visual communication. The multifaceted process of image enhancement involves the strategic manipulation of various image attributes, such as contrast, brightness, sharpness, and color balance, to accentuate desired features, correct imperfections, and heighten overall image fidelity.

In the spatial domain, enhancement techniques directly modify pixel values within the image, with popular methods including histogram equalization, contrast stretching, brightness adjustment, and sharpness enhancement. Histogram equalization, for instance, redistributes pixel intensity values across the histogram to achieve a more uniform distribution, consequently enhancing the contrast and visibility of details. Contrast stretching expands the range of pixel intensity values to maximize the contrast between light and dark regions, thereby enhancing image clarity. Brightness adjustment, meanwhile, alters the overall luminance levels to enhance visibility and perceptual quality. Additionally, sharpness enhancement techniques selectively augment contrast along edges and fine details, resulting in heightened clarity and definition.

In the frequency domain, techniques involve transforming an image into its frequency representation, where enhancement operations are performed before converting the image back to the spatial domain. Frequency domain techniques include frequency filtering and homomorphic filtering. Frequency filtering entails selectively attenuating or amplifying specific frequency components to enhance or suppress features. For instance, low-pass filters can mitigate high-frequency noise, while high-pass filters accentuate fine details. Homomorphic filtering corrects non-uniform illumination and contrast variations by decomposing the image into reflectance and illumination components, applying appropriate transformations, and recombining them to produce an enhanced image.

These enhancement techniques can be applied manually using image editing software or automated algorithms integrated into image processing tools. Leveraging these techniques effectively requires a deep understanding of the underlying image properties and the application domain. Furthermore, emerging techniques, such as machine learning-based approaches, are increasingly being used for image enhancement, providing the potential for more tailored and effective image enhancement solutions.

In conclusion, image enhancement constitutes a critical aspect of digital image processing, with significant implications in various applications. The choice of enhancement technique, image attribute, and domain can significantly impact image quality and interpretability. With the advent of new techniques and algorithms, the future of image enhancement looks promising, and it is likely to play an even more critical role in unlocking the potential of digital imagery.

Noise removal

Noise removal in image processing is a critical procedure aimed at reducing or eliminating unwanted artifacts and distortions that degrade the visual quality and fidelity of digital images. Noise is often introduced during image acquisition or transmission, manifesting as random variations in pixel values, resulting in undesirable graininess or distortion. The removal of such noise is imperative to restore image clarity, enhance interpretability, and facilitate accurate analysis and visualization. Various techniques are employed for noise removal, encompassing both spatial and frequency domain approaches.

In the spatial domain, techniques such as spatial filtering and edge-preserving filtering are commonly employed. Spatial filtering involves applying convolution masks or kernels to smooth pixel values while preserving image details. Various filter types, including mean filters, median filters, and Gaussian filters, are utilized to attenuate noise while preserving image features. Edge-preserving filters, such as bilateral filters and guided filters, selectively smooth regions with homogeneous intensity while preserving edges and contours, thereby maintaining image sharpness and clarity. However, these techniques may result in smoothing of image features and loss of image details.

In the frequency domain, noise removal techniques leverage the Fourier transform to analyze and manipulate image frequency components. Frequency filtering techniques, including low-pass, high-pass, and band-pass filtering, are used to attenuate specific frequency bands associated with noise while retaining essential image information. Low-pass filters, for instance, suppress high-frequency noise components, while high-pass filters accentuate fine details. Additionally, advanced techniques such as wavelet denoising and Wiener filtering exploit the multiscale representation of image details to effectively suppress noise across different frequency bands. Wavelet denoising decomposes the image into wavelet coefficients, attenuates noise in the coefficient domain, and reconstructs the denoised image. Wiener filtering, on the other hand, estimates the statistical properties of noise and signal to adaptively attenuate noise while preserving image features.

The selection of an appropriate noise removal technique depends on several factors, including the type and characteristics of noise, the desired level of noise suppression, and the impact on image features and details. Furthermore, the choice of a noise removal technique should be made judiciously to avoid excessive smoothing or loss of image information. The effectiveness of noise removal techniques can be evaluated using quantitative metrics such as signal-to-noise ratio (SNR) and peak signal-to-noise ratio (PSNR).

Noise removal techniques find widespread application across various fields, including medical imaging, remote sensing, surveillance, and digital photography, where it is essential to mitigate noise to enhance image quality, facilitate accurate analysis and interpretation, and improve the visual experience. With the emergence of new techniques and algorithms, the future of noise removal in image processing looks promising, and it is likely to play an even more critical role in unlocking the potential of digital imagery.

Image Sharpening

Sharpening in image processing serves as a crucial technique that enables the enhancement of image detail and clarity, thereby accentuating edges and fine features. This process involves selectively increasing the contrast along edges to make them appear crisper and more defined, ultimately leading to an overall improvement in image sharpness and visual quality. Sharpening proves to be particularly advantageous for images that appear soft or lacking in detail due to factors such as image blur, optical imperfections, or noise. With several methods available for sharpening in image processing, the most commonly utilized approach is unsharp masking. Unsharp masking entails the creation of a sharpened version of the image by subtracting a blurred version of the image from the original, thereby accentuating edges and details. This is achieved by applying a Gaussian blur filter to the original image, creating a smoothed version, subtracting this smoothed image from the original to obtain the high-frequency components, and then adding these high-frequency components back to the original image to create the sharpened result.

Another widely accepted sharpening technique is high-pass filtering, which involves the extraction of high-frequency components from the image using a high-pass filter, subsequently adding them back to the original image to enhance details. The selection of a sharpening technique is influenced by factors such as the characteristics of the image, the desired level of sharpening, and the trade-off between sharpening artifacts and the preservation of image details. While sharpening techniques are effective in enhancing image sharpness and detail, they may also amplify noise and introduce artifacts if applied excessively. It is, therefore, essential to apply sharpening judiciously and evaluate the results to ensure that the desired enhancement is achieved without compromising image quality. By effectively sharpening images, image processing practitioners can improve visual clarity, enhance interpretability, and elevate the overall quality of digital images across various domains, including photography, medical imaging, satellite imaging, and digital art.

Image Cropping

Cropping in image processing represents a fundamental technique that involves the selective removal of unwanted portions of an image to improve composition, focus attention on specific subjects, or resize the image to fit a desired aspect ratio. This versatile technique is primarily utilized to enhance the visual impact and communicative power of the image by removing distractions, adjusting the framing of a scene, or highlighting specific details. Additionally, cropping can also be employed for practical purposes such as resizing images for printing or digital display, or for optimizing images for specific applications such as social media or website banners.

The cropping process involves defining a rectangular or irregularly shaped region of interest within the original image and discarding the surrounding areas. Users can interactively adjust the size, aspect ratio, and position of the cropping region using cropping tools in image editing software until the desired composition is achieved. Once the cropping region is finalized, the software removes the areas outside the cropping region, resulting in a new image composed only of the selected region. In some cases, cropping may involve more advanced operations such as perspective correction or content-aware cropping, where the software automatically detects and removes unwanted elements while preserving important features within the cropping region.

Cropping is a powerful tool that enables photographers, designers, and artists to fine-tune composition, improve visual storytelling, and optimize images for various contexts and platforms. Appropriate usage of cropping can significantly enhance the visual appeal and communicative effectiveness of images,

allowing them to convey a clear and compelling message to viewers. It is, however, crucial to exercise caution when cropping images, as excessive cropping or improper composition can negatively impact the overall quality and impact of the image. Mastery over the art of cropping empowers image-processing practitioners to unlock new creative possibilities and elevate the quality of their visual creations across a wide range of applications.

(Bulb Light source)

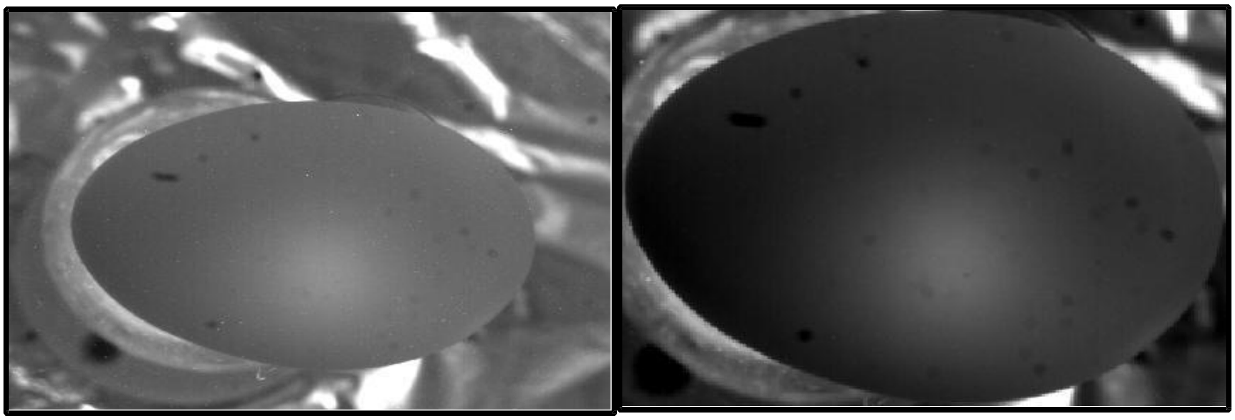


Figure 15 Enhanced and cropped egg Database

(Xenon Light source)

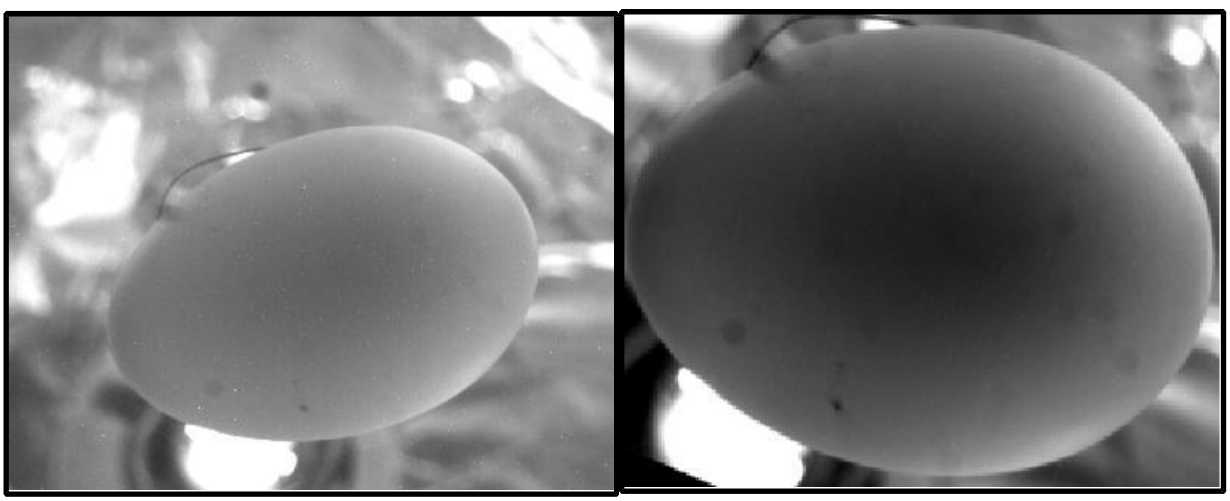


Figure 16 Enhanced and cropped egg Database

4.3 Feature Extraction & Classification

Egg quality assessment is a critical aspect of the egg industry, and leveraging advanced tools and techniques to obtain comprehensive insights into the physical and optical properties of eggs is essential. One such strategy is the use of multiple light sources to capture the egg's reflectance or absorption across different wavelengths. By illuminating the eggs with diverse light sources, researchers can obtain spectral information that offers insights into various optical properties. Conducting statistical analysis of the image data across different wavelengths adds another layer of depth to the analysis, providing valuable quantitative information about the spectral characteristics of the eggs.

Moreover, image processing techniques can be applied to extract spatial features from the multispectral images. Algorithms like edge detection, image segmentation, and texture analysis can delineate distinct regions of interest within the images and capture intricate spatial details. Edge detection algorithms identify abrupt changes in pixel intensity, highlighting boundaries and structural features of the eggs. Image segmentation algorithms partition the images into semantically meaningful regions, facilitating the isolation and characterization of different egg components. Texture analysis algorithms quantify textural patterns within the images, discerning subtle variations in surface properties such as roughness and granularity.

To fully leverage the multispectral images, state-of-the-art deep learning architectures like AlexNet, VGG16, and ResNet-18 can be employed. These convolutional neural networks (CNNs) excel at learning hierarchical representations of image data, capturing both low-level features like edges and textures and high-level semantic information. By training these networks on multispectral images, researchers can leverage their capacity to discern complex patterns and relationships across different wavelengths and spatial dimensions. The utilization of deep learning techniques enables automated feature extraction and classification, facilitating efficient and accurate egg quality prediction.

The integration of multiple light sources, statistical analysis of spectral data, image processing techniques, and deep learning methodologies presents a comprehensive approach to egg quality assessment. By synergistically leveraging these tools and techniques, researchers can unravel the intricate interplay between spectral and spatial features of eggs, leading to enhanced understanding and prediction of egg quality. Such an approach may have far-reaching implications in the egg industry, enabling the development of novel approaches for quality control and improving the efficiency and accuracy of egg grading systems.

Convolution Neural Networks (CNN)

Convolution Neural Networks (CNNs) represent a significant breakthrough in the field of machine learning, particularly in the domain of computer vision. CNNs are deep learning models designed to effectively process and analyze structured grid-like data, with images being the most common input. Unlike traditional neural networks, CNNs employ a hierarchical architecture consisting of specialized layers that extract hierarchical representations of visual data. The core building blocks of CNNs are convolutional layers, where learnable filters or kernels convolve across the input image, capturing local patterns and features. These convolutional operations are interleaved with pooling layers, which downsample the spatial dimensions of the feature maps, enabling hierarchical feature extraction while reducing computational complexity. Through the process of training on large datasets using supervised learning techniques, CNNs autonomously learn to extract hierarchical features from raw image data, progressively discerning complex visual patterns and structures. Additionally, CNN architectures often incorporate fully connected layers at the end of the network, which synthesizes the extracted features to produce the final output, such as class probabilities in image classification tasks.

Beyond their application in image classification, CNNs have been adapted to a wide range of computer vision tasks, including object detection, semantic segmentation, image generation, and more. Furthermore, CNNs have transcended the domain of computer vision and found utility in diverse fields like natural language processing, speech recognition, and even reinforcement learning. The versatility and efficacy of CNNs have solidified their position as a cornerstone of contemporary machine learning, empowering researchers and practitioners to tackle complex real-world problems with unprecedented accuracy and efficiency. As CNN continue to evolve, researchers are exploring novel architectures, training techniques, and applications to further extend their capabilities and push the boundaries of what is possible with deep learning. In conclusion, CNNs represent a pivotal advancement in machine learning and offer a promising avenue for addressing complex real-world challenges in a wide range of domains.

Convolutional Neural Networks (CNNs) have revolutionized the field of machine learning, particularly in the domain of computer vision. Inspired by the hierarchical organization of the visual cortex in the human brain, CNNs have been designed to learn and represent the hierarchical structure of visual data. By automatically learning hierarchical representations of data directly from raw inputs, CNNs eliminate the need for handcrafted feature engineering, making them highly flexible and applicable to diverse real-world scenarios. Furthermore, CNNs can leverage transfer learning, where pre-trained models are fine-tuned on smaller, domain-specific datasets, further enhancing their performance and generalization ability.

The impact of CNNs extends beyond traditional computer vision tasks, permeating various other domains of machine learning and artificial intelligence. CNNs have been applied to tasks like text classification, sentiment analysis, and language translation in natural language processing, where input data is represented as sequences of words or characters. Similarly, in speech recognition, CNNs have been employed to process spectrograms of audio signals, enabling accurate transcription and understanding of spoken language.

As CNNs continue to evolve, researchers are exploring novel architectures, training techniques, and applications to further push the boundaries of what is possible with deep learning. Attention mechanisms, capsule networks, and self-supervised learning represent some of the recent advancements, aiming to improve model interpretability, robustness, and efficiency. However, the ethical and societal implications of CNNs are increasingly being scrutinized, with efforts underway to address issues like bias, fairness, privacy, and accountability in the deployment of AI systems.

In conclusion, CNNs have transformed the landscape of machine learning, offering unparalleled capabilities for processing and understanding visual data. Their versatility, scalability, and effectiveness have catalyzed transformative advancements across a wide range of fields, driving progress and innovation in the era of artificial intelligence. As CNNs continue to evolve, it is essential to ensure that their deployment is ethical, fair, and transparent, benefiting society as a whole

AlexNet

AlexNet represents a seminal convolutional neural network (CNN) architecture that has played a decisive role in revolutionizing the field of computer vision and deep learning. Developed by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, AlexNet gained worldwide recognition after its remarkable success in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012, where it significantly outperformed traditional computer vision methods. The architecture of AlexNet is characterized by its deep and wide structure, consisting of eight layers, including five convolutional layers followed by three fully connected layers. Notably, AlexNet was among the first CNN architectures to incorporate multiple convolutional layers with rectified linear unit (ReLU) activations, which enabled faster convergence and mitigated the vanishing gradient problem. Additionally, AlexNet utilized techniques like local response normalization (LRN) and dropout regularization to prevent overfitting and improve generalization performance. The network was trained on the ImageNet dataset, which consists of millions of labeled images spanning thousands of categories, using the stochastic gradient descent (SGD) optimization algorithm with momentum. The success of AlexNet demonstrated the efficacy of deep learning in computer vision tasks, catalyzing a surge of interest and research in CNNs and paving the way for subsequent advancements in the field. Its legacy continues to endure, serving as a foundational reference point for the development of modern CNN architectures and deep learning techniques.

AlexNet's groundbreaking performance in the ImageNet competition marked a significant milestone in the advancement of deep learning and computer vision. Its success was attributed not only to its deep architecture but also to several key innovations that it introduced to the field. One such innovation was the utilization of GPU acceleration, which allowed AlexNet to efficiently train its large-scale neural network on the massive ImageNet dataset. This exploitation of GPU computing power enabled the training process to be significantly accelerated, reducing the training time from weeks to days. Furthermore, AlexNet introduced the concept of data augmentation, a technique where the training dataset is augmented with artificially generated variations of the original images, such as random crops, flips, rotations, and color shifts. This augmentation strategy helped prevent overfitting and improved the network's ability to generalize to unseen data.

Moreover, the architecture of AlexNet featured a novel design with a large number of learnable parameters, which enabled it to capture intricate patterns and features from raw image data effectively. The use of multiple convolutional layers allowed the network to learn hierarchical representations of visual features, gradually abstracting high-level concepts from low-level image features. Additionally, the incorporation of ReLU activations in the convolutional layers facilitated faster training convergence by mitigating the vanishing gradient problem, which had plagued deeper neural networks in the past. The adoption of local response normalization (LRN) also contributed to improving the network's performance by enhancing the contrast between different features and reducing the impact of covariate shifts during training.

AlexNet's impact transcended its victory in the ImageNet competition; it ignited a surge of interest and research in deep learning and CNNs across academia and industry. The success of AlexNet inspired the development of numerous subsequent CNN architectures, each building upon its foundational principles and innovations. Today, deep learning-powered computer vision systems are ubiquitous, powering applications ranging from autonomous vehicles and medical imaging to facial recognition and augmented reality. Thus, AlexNet's pioneering contributions have left an indelible mark on the field of machine learning, shaping its trajectory and paving the way for transformative advancements in artificial intelligence.

VGG-16

VGG16, or Visual Geometry Group 16, is a convolutional neural network that has significantly contributed to the field of computer vision. its remarkable performance on various visual recognition tasks has made it a widely recognized architecture. VGG16's architecture is characterized by its depth, consisting of 16 layers, including 13 convolutional layers and three fully connected layers. Its notable feature is the use of smaller convolutional filters (3x3) with a fixed padding size and a stride of one, which helps in capturing spatial hierarchies of visual features more efficiently.

The uniformity of VGG16's architecture, where convolutional layers are stacked on top of each other with a consistent filter size and stride, enables better interpretability and understanding of the network's behavior. Additionally, the network employs ReLU activations after each convolutional layer, which enable it to learn more complex and expressive representations of the input data. Furthermore, VGG16 utilizes dropout regularization in the fully connected layers to prevent overfitting and improve generalization performance.

VGG16's success in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2014, where it demonstrated state-of-the-art performance in image classification tasks, has made it a popular choice for transfer learning in various computer vision applications. Pre-trained VGG16 models on large-scale datasets like ImageNet can be fine-tuned on specific tasks or datasets with limited training data, enabling rapid development of high-performance models with minimal computational resources.

Despite its effectiveness, VGG16 has limitations in terms of computational efficiency and memory requirements due to its deep and dense architecture. However, its contributions to the field of deep learning are noteworthy, serving as a foundational reference point for subsequent advancements and inspiring further research in computer vision and beyond.

The VGG16 architecture has made a profound impact on the field of deep learning and computer vision, serving as a cornerstone for researchers and practitioners alike. Its widespread adoption across a range of computer vision tasks, including image classification, object detection, and semantic segmentation, is a testament to its simplicity and effectiveness.

One of the key contributions of VGG16 lies in its ability to learn hierarchical representations of visual features through the stacking of convolutional layers. By capturing increasingly abstract features from raw input data, VGG16 can effectively capture the underlying structure and semantics of images, enabling accurate predictions on diverse datasets. Moreover, the modular and uniform architecture of VGG16 allows researchers to modify and extend the network for specific applications or research objectives, facilitating experimentation and exploration.

The availability of pre-trained VGG16 models on large-scale datasets like ImageNet has democratized access to state-of-the-art computer vision capabilities, empowering researchers and developers to leverage transfer learning for their own projects. VGG16's impact extends beyond its performance in the ImageNet challenge, with its contributions serving as a foundational reference point for subsequent advancements in the field.

Despite its effectiveness, VGG16's deep and dense architecture presents challenges in terms of computational efficiency and memory requirements, particularly when deployed on resource-constrained devices or in real-time applications. Ongoing research efforts have focused on exploring alternative CNN architectures and optimization techniques to improve efficiency without sacrificing performance. These efforts have led to the development of streamlined architectures like MobileNet, EfficientNet, and SqueezeNet, which are specifically designed for deployment on mobile devices and edge computing platforms.

In summary, VGG16 represents a significant milestone in the evolution of deep learning and computer vision, with its contributions informing and inspiring future advancements in the field. As the field of deep learning continues to evolve, VGG16's legacy will endure, driving progress in artificial intelligence and shaping the future of computer vision

ResNet-18

ResNet-18 is a specific variant of the Residual Network (ResNet) architecture, which has significantly contributed to advancing deep learning, especially in the realm of computer vision. Developed by Kaiming He and his colleagues at Microsoft Research, ResNet-18 is characterized by its depth, efficiency, and effectiveness in learning representations from visual data. At its core, ResNet-18 employs a deep convolutional neural network (CNN) structure with 18 layers, including convolutional layers, batch normalization, ReLU activations, and max-pooling layers. What distinguishes ResNet-18 from its predecessors is the introduction of residual connections, also known as shortcut connections, within its architecture. These connections allow information to bypass certain layers, enabling the network to learn residual mappings instead of attempting to directly fit the desired underlying mapping. This innovation addresses the challenge of training very deep networks by alleviating the vanishing gradient problem and enabling smoother flow of gradients during backpropagation. ResNet-18 comprises a series of residual blocks, each containing multiple convolutional layers, where the residual connections facilitate the efficient learning of complex features. As a result, ResNet-18 achieves state-of-the-art performance on various image classification benchmarks like ImageNet, demonstrating superior accuracy and robustness compared to earlier architectures. Its compact design and remarkable performance have made ResNet-18 a cornerstone in the field of deep learning, serving as a go-to model for a wide range of computer vision tasks, from object recognition to image segmentation, and even transfer learning in domains beyond vision.

ResNet-18's impact extends beyond its performance in image classification tasks. Its architectural principles, particularly the use of residual connections, have inspired subsequent advancements in deep learning architectures. By enabling the training of much deeper networks, ResNet-18 has paved the way for the development of even more complex models capable of learning hierarchical representations from vast amounts of data. Moreover, ResNet-18's success has led to the exploration of transfer learning techniques, where pre-trained ResNet-18 models on large datasets like ImageNet are fine-tuned for specific tasks with smaller labeled datasets, thereby accelerating the development of machine learning solutions in various domains. Furthermore, ResNet-18's efficiency in terms of computational resources and memory footprint has made it accessible for deployment on resource-constrained devices, facilitating the integration of deep learning into applications such as mobile devices, IoT devices, and edge computing systems. In research, ResNet-18 serves as a benchmark model for evaluating the performance of novel architectures and algorithms, driving continuous innovation in the field of deep learning. Overall, ResNet-18's significance transcends its role as a state-of-the-art image classification model; it symbolizes a breakthrough in deep learning methodology, empowering researchers and practitioners to tackle increasingly complex tasks across diverse domains with confidence and efficiency.

CHAPTER - 5

EXPERIMENTAL EVALUATION AND RESULTS

5. Experimental Evaluation and Results.

The experimental evaluation was performed on the generated database (captured using a CMOS camera and LCTF in the range of 400nm to 720nm), having information of 17 wavelengths. This database contains the images of 30 egg samples (good and bad), three images per spectra, resulting in a total of 3,060 images. Of these images, 1,530 were captured using the incandescent light bulb, including 918 good egg images and 612 bad egg images. The same was calculated for the xenon bulb. After obtaining a total of 3,060 images using both incandescent and xenon bulbs for good and bad eggs, a technique called feature extraction and classification was applied to these images. The images were then separated into a training dataset and a testing dataset, with 70% of the database given for training (54 samples) and 30% for testing (26 samples). The training dataset consisted of 54 samples, as for each egg, three images were taken, resulting in a total of 18 eggs and 54 images. The testing dataset consisted of 26 samples, as for each egg, three images were taken, resulting in a total of 12 eggs and 26 images.

The train and test images were preprocessed using, Image adjustment, alignment, Enhancement, noise removal, sharpening, and cropping For the feature extraction and classification of good and bad eggs we have employed Alexnet, vgg16 and ResNet.18 . The results of the same are tabulated as follows.

5.1 Result

spectrum	Alexnet	VGG.16	ResNet.18
500	96.12	92	90.35
520	88.46	100	96.47
540	100	95	87.09
560	73.08	100	90.28
580	90.00	92.15	87.69
600	100	97.15	92.22
620	100	90.17	85.37
640	100	100	85.25
660	100	80.27	100
680	100	92.33	95.23
700	96.15	100	87.17
720	96.15	100	100

Table 2 Result using AlexNet,VGG.16,ResNet.18

From table no 5.1 it represents the accuracy of three convolutional neural network (CNN) models AlexNet, VGG-16, and ResNet-18 across various spectral bands ranging from 500 nm to 720 nm. AlexNet demonstrates the most consistent and high performance, achieving perfect accuracy (100%) in multiple spectral bands, including 540 nm, 600 nm, 620 nm, 640 nm, 660 nm, and 680 nm. It also maintains high accuracy above 96% at 500 nm, 700 nm, and 720 nm. However, it drops to its lowest accuracy of 73.08% at 560 nm.

On the other hand, VGG-16 exhibits perfect accuracy at 520 nm, 560 nm, 640 nm, and 720 nm. It also maintains high accuracy in other bands, such as 540 nm (95%), 580 nm (92.15%), 600 nm (97.15%), 680 nm (92.33%), and 700 nm (100%). Despite these strengths, it has its lowest accuracy at 660 nm, with an accuracy of 80.27%.

ResNet-18 shows a more variable performance. It achieves perfect accuracy at 660 nm and 720 nm and performs well at 520 nm (96.47%) and 680 nm (95.23%). However, it shows lower accuracy in several bands, particularly at 620 nm (85.37%) and 640 nm (85.25%).

In summary, AlexNet is the most robust model, excelling across the majority of spectral bands with the highest and most consistent accuracies. VGG-16 also performs exceptionally well, particularly at specific bands, but with greater variability compared to AlexNet. ResNet-18, while achieving high accuracy in some bands, generally shows more fluctuations, making it the least consistent among the three models. This comparative analysis underscores AlexNet's superiority for multispectral egg quality assessment, followed closely by VGG-16 and then ResNet-18.

5.2 Graph

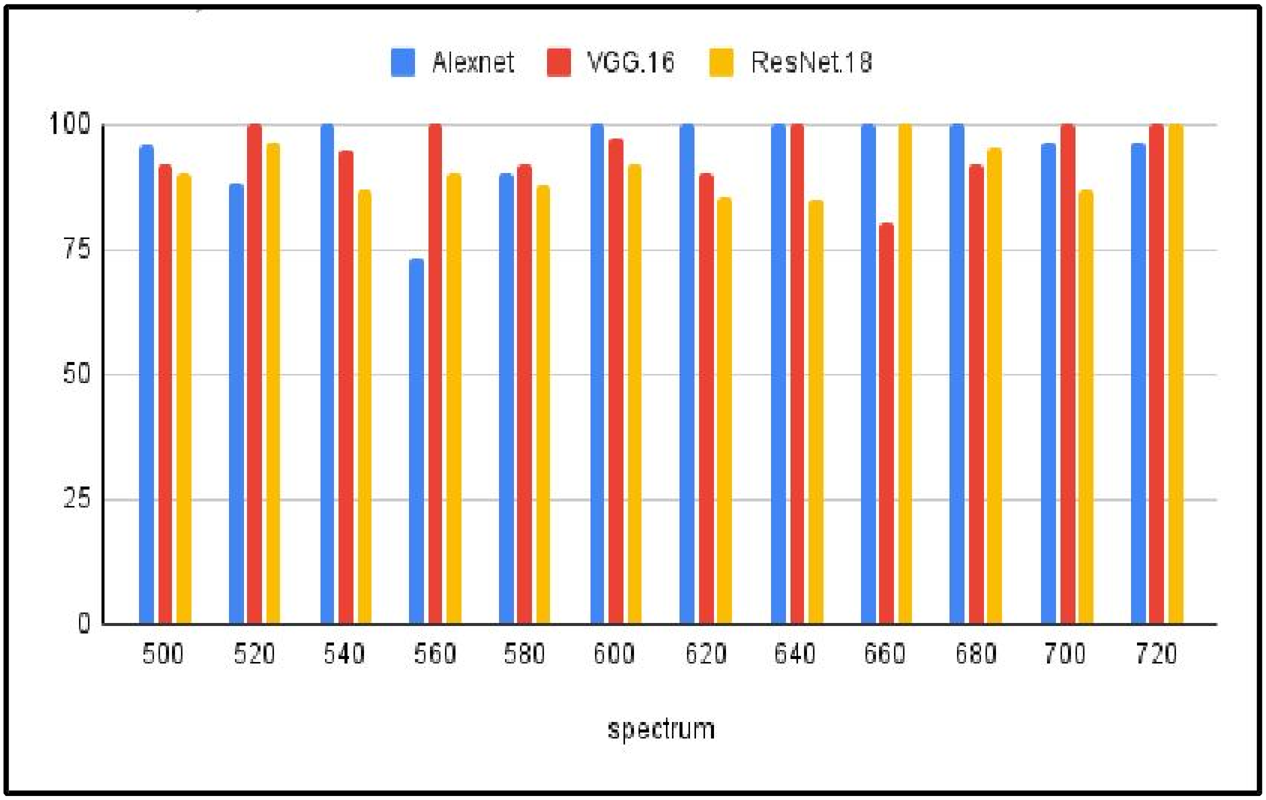
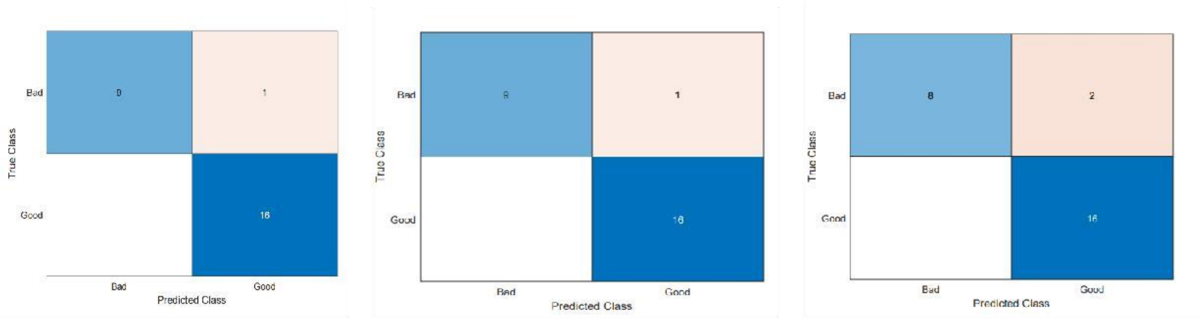


Figure 17 Spectrum vs Accuracy

\

The graph 5.2 compares the performance of AlexNet, VGG.16, and ResNet.18 for image recognition across the visible spectrum. AlexNet performs best overall, and VGG-16 also performs exceptionally well while resNet.18 lags behind. It's important to note that the accuracy of these techniques depends on the training data and the nature of the images being classified.

5.3 Confusion Matrix



AlexNet(500nm) VGG16(500nm) ResNet18(500nm)

22

Figure 18 Result showing Confusion Matrix

The confusion matrix you provided offers insights into the performance of a multispectral egg quality classification system separating good and bad eggs. Here, 80% (54 samples) were used for training, and the remaining 20% (26 samples) were used for testing.

Looking at the matrix, we see positive results along the diagonal. 16 good eggs were correctly classified (True Positives), and 7 bad eggs were identified accurately (True Negatives). There were a few misclassifications, though. One bad egg was mistakenly labeled good (False Positive), These errors could be due to the inherent similarity of some bad eggs to good eggs, or potential issues during data collection or labeling.

Overall, the model performed well, with a high number of correctly classified good and bad eggs (TP and TN). To further enhance the system, consider these aspects:

- Class Imbalance: If the training data has significantly more good eggs than bad eggs, the model might favor classifying everything as good. Balancing the data or using techniques to address this imbalance could improve performance.
- Test Set Size: A larger test set (more than 26 samples) would provide statistically stronger results for evaluating the model's generalizability.

Future Outlook

- Detailed Yolk and Albumen Analysis: Multispectral imaging can differentiate between various qualities of yolk and albumen, such as their color, density, and consistency, ensuring only high-quality components reach consumers.
- Detection of Internal Contaminants: It can identify internal contaminants like blood spots, meat spots, or bacterial infections that are not visible externally.

References

1. Anca Galiş, Dale, L., Christelle Boudry, & André Thewis. (2012). *The potential use of Near-Infrared spectroscopy for the quality assessment of eggs and egg products*. *58*(3), 285–298.
2. Ketelaere, B. D., Bamelis, F., Kemps, B., Decuypere, E., & Baerdemaeker, J. D. (2004). Non-destructive measurements of the egg quality. *World's Poultry Science Journal*, *60*(3), 289–302. https://doi.org/10.1079/WPS200417
3. Hüseyin Güray Çiftçi, Gonca Bilge, & Ezgi Aytaç. (2024). Monitoring the quality changes and freshness assessment of eggs based on chemometrics method. *Journal of Food Process Engineering*, *47*(3). https://doi.org/10.1111/jfpe.14591
4. Akowuah, T. O. S., Teye, E., Hagan, J., & Nyandey, K. (2020). Rapid and Nondestructive Determination of Egg Freshness Category and Marked Date of Lay using Spectral Fingerprint. *Journal of Spectroscopy*, *2020*, 1–11. https://doi.org/10.1155/2020/8838542
5. Kim, J., Semyalo, D., Rho, T.-G., Bae, H., & Cho, B.-K. (2022). Non-Destructive Detection of Abnormal Chicken Eggs by Using an Optimized Spectral Analysis System. *Sensors*, *22*(24), 9826–9826. https://doi.org/10.3390/s22249826
6. Qi, L., Zhao, M., Li, Z., Shen, D., & Lu, J. (2020). Non-destructive testing technology for raw eggs freshness: a review. *SN Applied Sciences*, *2*(6). https://doi.org/10.1007/s42452-020-2906-x
7. Yao, K., Sun, J., Cheng, J., Chen, C., & Zhou, X. (2022). Nondestructive detection of S-ovalbumin content in eggs using portable NIR spectrometer and

MPA-CARS. *Journal of Food Process Engineering*, *46*(1). https://doi.org/10.1111/jfpe.14186

8. @Journal Article{ Journal Article, title={ Non-Destructive Detection of Abnormal Chicken Eggs by Using an Optimized Spectral Analysis System }, authors={ Juntae Kim and Dennis Semyalo and Tae-Gyun Rho and Hyungjin Bae and Byoung-Kwan Cho }, journal={ Sensors }, year={ 2022 }, volume={ 22 }, pages={ 9826-9826 }, number={ 24 }, doi={ 10.3390/s22249826 }, }
9. @Patent{ Patent, title={ Rapid nondestructive detection system and method for freshness of eggs }, authors={ Wang Qiaohua and Yuan Cheng and Yu Xianqiao and Li Li }, year={ 2018 }, }
10. @Patent{ Patent, title={ Egg online nondestructive detection system }, authors={ Rong Weiyi and Jia Yunfei }, year={ 2019 },
11. @Patent{ Patent, title={ Method for egg freshness non-destructive detection based on centroid measurement }, authors={ Duan Xiang and Wen Tan and Liu Xuebo and Lan Ying and Qinjun Zhang and Lu Yang }, year={ 2020 },
12. @Patent{ Patent, title={ Egg detection method based on detection and sorting device for egg quality distinguishing }, authors={ Xu Yedong and Xu Chunlei and Xu Jiagang }, year={ 2017 },
13. @Journal Article{ Journal Article, title={ Detection of infertile eggs using visible transmission spectroscopy combined with multivariate analysis }, authors={ Md. Hamidul Islam and Naoshi Kondo and Yuichi Ogawa and Tateshi Fujiura and Tetsuhito Suzuki and Shinichi Fujitani }, journal={ Engineering in agriculture, environment and food }, year={ 2017 }, publisher={ No longer published by

Elsevier }, volume={ 10 }, pages={ 115-120 }, number={ 2 }, doi={ 10.1016/J.EAEF.2016.12.002 }, }

14. @Patent{ Patent, title={ Egg quality nondestructive detection method based on unit weight of egg }, authors={ Li Xingmin and You Ziqian and Xu Lei }, year={ 2018 },
15. @Journal Article{ Journal Article, title={ Non-Destructive Measurement of Egg's Haugh Unit by Vis-NIR with iPLS-Lasso Selection }, authors={ Lei-ming Yuan and Xueping Fu and Xiaofeng Yang and Xiaojing Chen and Guangzao Huang and Xi Chen and Wenxuan Shi and Limin Li }, journal={ Foods }, year={ 2023 }, volume={ 12 }, pages={ 184-184 }, number={ 1 },
16. Loffredi, E., Grassi, S., & Alamprese, C. (2021). Spectroscopic approaches for non-destructive shell egg quality and freshness evaluation: Opportunities and challenges. *Food Control*, *129,* 108255. https://doi.org/10.1016/j.foodcont.2021.108255
17. Lin, H., Zhao, J., Sun, L., Chen, Q., & Zhou, F. (2011). Freshness measurement of eggs using near infrared (NIR) spectroscopy and multivariate data analysis. *Innovative Food Science & Emerging Technologies*, *12*(2), 182–186. https://doi.org/10.1016/j.ifset.2011.01.008
18. Ketelaere, B. D., Bamelis, F., Kemps, B., Decuypere, E., & Baerdemaeker, J. D. (2004b). Non-destructive measurements of the egg quality. *World's Poultry Science Journal*, *60*(3), 289–302. https://doi.org/10.1079/WPS200417
19. Dai, D., Jiang, T., Lu, W., Shen, X., Xiu, R., & Zhang, J. (2020). Nondestructive Detection for Egg Freshness Based on Hyperspectral Scattering Image Combined

with Ensemble Learning. *Sensors*, *20*(19), 5484. https://doi.org/10.3390/s20195484

20. https://www.researchgate.net/publication/283112601_Determination_of_egg_quality_characteristics_of_different_poultry_species_with_digital_image_analysis

Annexure

Code

#AlexNet

#Script to employ pre-trained network two class problem

```
clear all; clear memory; clc;
disp('Running QTH-QTH Lighting')
% cd('./QTH-QTH/')
% bandName = 'Band6';
```

Load Pre-trained network and define the layers

```
net = alexnet;
layers = net.Layers;
num_Train_class = 2;
layers(23) = fullyConnectedLayer(num_Train_class);
layers(25) = classificationLayer;
```

```
%% Iteration -number of trails
for i=1:10
    disp('Iteration_');
    disp(i);
    rootFolder = strcat('C:\Users\admin\Desktop\vishal\Training_Testing_Data\720\Train');
    imds_train = imageDatastore(rootFolder, 'IncludeSubfolders', true, 'LabelSource',
'foldernames');
    imds_train.ReadFcn = @readFunctionTrainGrey;
```

DEFINE TRAINING OPTIONS

```
opts = trainingOptions('sgdm', ...
    'InitialLearnRate', 0.001, ...
    'Verbose',false, ...
    'MaxEpochs',7, ...  %epochs has been changed
    'Shuffle','every-epoch','verbose',true,...
    'Plots','training-progress');

% options = trainingOptions('sgdm', ...
%     'MiniBatchSize',10, ...
%     'MaxEpochs',100, ...
%     'InitialLearnRate',1e-4, ...
%     'Shuffle','every-epoch', ...
%     'ValidationData',augimdsValidation, ...
%     'ValidationFrequency',3, ...
%     'Verbose',false, ...
```

```
%     'Plots','training-progress');
```

TRAIN NETWORK

```
 [convNet, info] = trainNetwork(imds_train, layers, opts);
```

LOAD TEST DATA and Perform classification

```
rootFolder = strcat('C:\Users\admin\Desktop\vishal\Training_Testing_Data\640\Test');
imds_test = imageDatastore(rootFolder, 'IncludeSubfolders', true, 'LabelSource', 'foldernames');
imds_test.ReadFcn = @readFunctionTrainGrey;

% Classification and accuracy
[labels, score] = classify(convNet, imds_test);
confMat = confusionmat(imds_test.Labels, labels);
confMat = confMat./sum(confMat,2);
accuracy(i) = mean(diag(confMat));
end
   % matObj = matfile('QTH_QTH_accuracy_Alex.mat');
   % m = matfile('QTH_QTH_accuracy_Alex.mat','Writable',true);
   % m.accuracyBand1=accuracy;
   % m.Band1std=std(accuracy)
   % m.accuracyBand1avg=mean(accuracy)
   % toc;
acc=mean(accuracy)
```

Function to resize the image as per the requirement of network

```
function I = readFunctionTrainGrey(filename)
% Resize the images to the size required by the network.
I = imread(filename);
I = imresize(I, [227 227]);
I=repmat(I, [1,1,3]);
end
```

#VGG 16

#Script to employ pre-trained network two class problem

```
clear; clear memory; clc;
disp('Running QTH-QTH Lighting')
% cd('./QTH-QTH/')
% bandName = 'Band6';
```

Load Pre-trained network and define the layers

```
net = vgg16;
layers = net.Layers;
layers(39) = fullyConnectedLayer(2);
layers(41) = classificationLayer;
```

```
%% Iteration -number of trails
for i=1:2
    disp('Iteration_');
    disp(i);
    rootFolder = strcat('C:\Users\admin\Desktop\vishal\Training_Testing_Data\720\Train');
    imds_train = imageDatastore(rootFolder, 'IncludeSubfolders', true, 'LabelSource',
'foldernames');
    imds_train.ReadFcn = @readFunctionTrainGrey;
```

DEFINE TRAINING OPTIONS

```
opts = trainingOptions('sgdm', ...
    'MiniBatchSize',32, ...
    'InitialLearnRate', 0.001, ...
    'Verbose',false, ...
    'MaxEpochs',7, ...  %epochs has been changed
     'Shuffle','every-epoch',...
    'Plots','training-progress');

% options = trainingOptions('sgdm', ...
%     'MiniBatchSize',10, ...
%     'MaxEpochs',100, ...
%     'InitialLearnRate',1e-4, ...
%     'Shuffle','every-epoch', ...
%     'ValidationData',augimdsValidation, ...
%     'ValidationFrequency',3, ...
%     'Verbose',false, ...
%     'Plots','training-progress');
```

TRAIN NETWORK

```
 [convNet, info] = trainNetwork(imds_train, layers, opts);
```

LOAD TEST DATA and Perform classification

```
rootFolder = strcat('C:\Users\admin\Desktop\vishal\Training_Testing_Data\640\Test'); %'Test';
imds_test = imageDatastore(rootFolder, 'IncludeSubfolders', true, 'LabelSource', 'foldernames');
imds_test.ReadFcn = @readFunctionTrainGrey;

% Classification and accuracy
[labels, score] = classify(convNet, imds_test);
confMat = confusionmat(imds_test.Labels, labels);
confMat = confMat./sum(confMat,2);
accuracy(i) = mean(diag(confMat));
end
    % matObj = matfile('QTH_QTH_accuracy_Alex.mat');
    % m = matfile('QTH_QTH_accuracy_Alex.mat','Writable',true);
    % m.accuracyBand1=accuracy;
    % m.Band1std=std(accuracy)
    % m.accuracyBand1avg=mean(accuracy)
    % toc;
```

```
acc=mean(accuracy)
```

Function to resize the image as per the requirement of network

```
function I = readFunctionTrainGrey(filename)
% Resize the images to the size required by the network.
I = imread(filename);
I = imresize(I, [224 224]);
I=repmat(I, [1,1,3]);
end
```

#ResNet 18

#Script to employ pre-trained network two class problem

```
clear all; clear memory; clc;
disp('Running QTH-QTH Lighting')
% cd('./QTH-QTH/')
% bandName = 'Band6';
```

Load Pre-trained network and define the layers

```
net = resnet18;

Feature_Learner = net.Layers(69);
Output_Classifier = net.Layers(71);

Number_of_Classes = 2;
New_Feature_Learner = fullyConnectedLayer(Number_of_Classes,...
    "Name",'Gender_feature',"WeightLearnRateFactor",10,"BiasLearnRateFactor",10);
New_Classifier_Layer = classificationLayer("Name","Gender classifier");
Layer_Graph = layerGraph(net);
New_Layer_Graph = replaceLayer(Layer_Graph, Feature_Learner.Name,New_Feature_Learner);
New_Layer_Graph = replaceLayer(New_Layer_Graph,Output_Classifier.Name,
New_Classifier_Layer);
%analyzeNetwork(New_Layer_Graph)
```

```
%% Iteration -number of trails
for i=1:2
    disp('Iteration_');
    disp(i);
    rootFolder = strcat('C:\Users\admin\Desktop\2024_M.Sc.
Data\VISHAL\vishal\Training_Testing_Data\560\Train');
    imds_train = imageDatastore(rootFolder, 'IncludeSubfolders', true, 'LabelSource',
'foldernames');
    imds_train.ReadFcn = @readFunctionTrainGrey;
```

DEFINE TRAINING OPTIONS

```
opts = trainingOptions('sgdm', ...
    'InitialLearnRate', 0.001, ...
    'Verbose',true, ...
    'MaxEpochs',7, ...  %epochs has been changed
     'Shuffle','every-epoch','Verbose',true);%, ...
%     'Plots','training-progress');

% options = trainingOptions('sgdm', ...
%     'MiniBatchSize',10, ...
%     'MaxEpochs',100, ...
%     'InitialLearnRate',1e-4, ...
%     'Shuffle','every-epoch', ...
%     'ValidationData',augimdsValidation, ...
%     'ValidationFrequency',3, ...
%     'Verbose',false, ...
%     'Plots','training-progress');
```

TRAIN NETWORK

```
 [convNet, info] = trainNetwork(imds_train, New_Layer_Graph , opts);
```

LOAD TEST DATA and Perform classification

```
rootFolder = strcat('C:\Users\admin\Desktop\2024_M.Sc.
Data\VISHAL\vishal\Training_Testing_Data\560\Test'); %'Test';
imds_test = imageDatastore(rootFolder, 'IncludeSubfolders', true, 'LabelSource', 'foldernames');
imds_test.ReadFcn = @readFunctionTrainGrey;

% Classification and accuracy
[labels, score] = classify(convNet, imds_test);
confMat = confusionmat(imds_test.Labels, labels);
confMat = confMat./sum(confMat,2);
accuracy(i) = mean(diag(confMat));
end
    % matObj = matfile('QTH_QTH_accuracy_Alex.mat');
    % m = matfile('QTH_QTH_accuracy_Alex.mat','Writable',true);
    % m.accuracyBand1=accuracy;
    % m.Band1std=std(accuracy)
    % m.accuracyBand1avg=mean(accuracy)
    % toc;
acc=mean(accuracy)
```

Function to resize the image as per the requirement of network

```
function I = readFunctionTrainGrey(filename)
% Resize the images to the size required by the network.
I = imread(filename);
I = imresize(I, [224 224]);
```

```
I=repmat(I, [1,1,3]);
end
```