Heaven's Light is Our Guide

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

Rajshahi University of Engineering & Technology, Bangladesh

Bloodstain Classification in Forensic Analysis Using Optimized 3D CNN

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CERTIFICATE

This is to certify that this thesis report entitled ***"Bloodstain Classification in Forensic Analysis Using Optimized 3D CNN "*** *submitted by* ***Md Al Amin Tokder , Roll:1803078*** *in partial fulfillment of the requirement for the award of the degree of Bachelor of Science in Department of Computer Science & Engineering of Rajshahi University of Engineering & Technology, Bangladesh is a record of the candidate own work carried out by him under my supervision. This thesis has not been submitted for the award of any other degree.*

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ABSTRACT

Blood stain detection is essential in crime scene analysis as it provides valuable insights into the events that transpired, aids in identifying individuals involved and supports the investigation process of criminal cases. It helps investigators understand what happened, who was involved and when it oc- curred. Advancements in forensic science, particularly bloodstain analysis, have become imperative for enhancing crime scene re- construction. Conventional methods like DNA analysis, chemical analysis often takes more time to identify bloodstain. Instead of DNA analysis this research contributes to the advancement of forensic science by introducing an innovative approach to bloodstain identification and classification by using a 3D CNN model utilizing the capabilities of Hyperspectral Imaging. Here we introduce an optimized 3D CNN with mish activation function and finding the best accuracy. This work will help to make faster investigations of forensic scene analysis and analyzing criminal cases. By applying the optimized 3D CNN model we got outperforms of the existing CNN model.We got 97% accuracy which is higher than the existing 3D CNN (95%) and hybrid CNN(96%) model and parameters are reduced from 291895 to 125943

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Chapter 1

Introduction

1.1 Introduction

In Dynamic criminal investigation, the field of forensic science plays a pivotal role in collecting, detecting, and analyzing evidence to facilitate successful case resolution. The examination of body fluids, particularly bloodstains holds significant importance during violent crime scenes as an integral aspect of forensic science [1, 2, 3, 4]. The existences of blood at such scenes makes it a valuable forensic evidence, presenting challenges and opportunities for thorough analysis. Collecting, detecting and analyzing evidence from a crime scene is extremely challenging for a successful and active criminal investigation[5].

Body fluids are considered a crucial asset in forensic inquiries, especially in violent crime scenes. Among these, blood holds the highest importance in forensic analysis [6]. To identify bloodstain and the age of the bloodstains are crucial for solving a problem. By looking at how blood is spread out, we can understand what happened during the crime and maybe even identify who was involved in crime. Determining the age of bloodstains helps us piece together the timeline of events, which is important for finding suspects[7].

Blood evidence plays a pivotal role in the investigation and reconstruction of crime scenes. This type of biological evidence is invaluable for linking a suspect to a crime or for excluding someone from suspicion. To fully appreciate the importance and the challenges associated with blood evidence in forensic contexts, it is essential to explore its identification, classification, and the innovative technologies emerging to enhance these processes.

1.1.1 Blood Identification and Classification

Blood evidence at a crime scene typically involves identifying bloodstains and classifying them based on type and origin. This process begins with presumptive tests to confirm whether a substance is blood. Once confirmed, further tests are conducted to determine the species (human or animal) and then to identify the blood type. These tests are critical because they can connect a blood sample from a crime scene to a specific individual through DNA profiling.

The traditional methods for blood classification involve a series of chemical and serological tests. For example, the Kastle-Meyer test uses phenolphthalein and hydrogen peroxide to detect hemoglobin. A positive reaction (a pink color) indicates the presence of blood. Further serological testing can distinguish human blood from animal blood, and subsequent DNA analysis can match the blood to a specific individual, providing a powerful tool for law enforcement.

However, the process of blood identification is not without its challenges. Chemical tests, while useful, can sometimes compromise the DNA within the blood, particularly if the blood is exposed to harsh chemicals or environmental conditions that degrade genetic material. This degradation can make it difficult to obtain a clear genetic profile, which is crucial for conclusive forensic analysis.

Blood identification and classification in forensic science are crucial for determining the source and nature of bloodstains found at a crime scene, which can be pivotal in solving criminal cases. Blood identification involves determining whether a substance is blood or not, while classification goes a step further to determine the species from which the blood originates and, if possible, the individual to whom it belongs.

The process begins with presumptive tests to ascertain the presence of blood. These tests, such as the Kastle-Meyer test, use chemical reagents that react with hemoglobin to produce a color change indicating the presence of blood. Luminol and fluorescein are other common chemicals used in these tests, which cause the blood to luminesce under specific conditions, making it easier to identify traces of blood that are invisible to the naked eye.

Following presumptive tests, confirmatory tests are employed to definitively prove the presence of blood. These include the Takayama and Teichmann tests, which involve crystallization techniques to visually confirm blood's presence. Microscopic examination can also identify specific blood cells, further confirming the test's findings.

The classification phase involves more sophisticated methods such as ABO typing, which categorizes blood based on the presence or absence of antigens in red blood cells. Further genetic analysis, such as DNA profiling, can not only confirm the species but also potentially identify the individual from whom the blood came. Such DNA analysis involves extracting DNA from the blood and comparing it to known DNA samples, either from suspects or from databases like CODIS (Combined DNA Index System).

1.2 Challenges in Traditional Blood Analysis

Traditional methods of analyzing blood at crime scenes can be invasive and potentially destructive. Chemical tests may alter the physical and chemical properties of bloodstains, complicating the interpretation of results. For example, luminol, commonly used to detect trace amounts of blood, is known for its luminescence; however, it can also dilute blood samples, making subsequent DNA extraction and analysis more problematic.

Additionally, the process of collecting and analyzing blood evidence can be time-consuming and requires significant expertise. Incorrect handling or analysis can lead to contamination or misinterpretation of evidence, which can severely impact a criminal investigation.

Blood analysis, especially involving DNA and chemical methods, faces several challenges that can complicate forensic investigations. One primary challenge is the degradation of DNA in blood samples due to environmental factors such as heat, moisture, or microbial action. This degradation can fragment the DNA, making it difficult to obtain a complete and accurate profile. Chemical analysis of blood can also be problematic when the blood is mixed with other substances, which can interfere with the reactions used in presumptive and confirmatory tests. For example, the presence of bleach or other cleaning chemicals can either destroy the blood or produce false positives in tests like the Kastle-Meyer reaction.

Another challenge is the sensitivity of these tests. While highly sensitive tests can detect trace amounts of blood, they are also more susceptible to contamination. This contamination can come from the environment or from the personnel conducting the analysis, leading to misleading results or misidentification.

Furthermore, the limited quantity of blood available at a crime scene can restrict the extent of testing that can be performed. Each test consumes some of the sample, and when only small quantities are available, prioritizing which tests to perform can be critical but challenging.

1.2.1 Hyperspectral Imaging (HSI) in Forensic Science

To address these challenges, forensic scientists are turning to more advanced technologies, such as Hyperspectral Imaging (HSI). HSI is a technique that involves capturing and analyzing a wide spectrum of light beyond what the human eye can see. Each pixel in a hyperspectral image contains a continuous spectrum of light, which allows for detailed analysis of the material properties of an object, including bloodstains.

Hyperspectral imaging (HSI) is a technological advancement in forensic science that offers significant improvements over traditional methods of blood analysis. HSI involves capturing and analyzing a wide spectrum of light beyond what the human eye can see, from the ultraviolet (UV) to the near-infrared (NIR). Each substance, including different types of blood and bodily fluids, has a unique spectral signature, which HSI can detect and analyze.

HSI's ability to scan a crime scene remotely (e.g., without direct contact with the evidence) reduces the risk of contamination. This technology can analyze bloodstains on a variety of surfaces, even those that are colored or patterned, where traditional methods might fail.

Another advantage of HSI is its non-destructive nature, allowing forensic analysts to preserve the original evidence while still performing thorough analyses. This is particularly important in cases where evidence is limited or needs to be preserved for future reexamination.

The Emergence of Hyperspectral Imaging

To overcome the limitations posed by traditional methods, forensic researchers have turned to more advanced technologies, one of which is Hyperspectral Imaging (HSI). HSI is a technology adapted from remote sensing and has been gaining ground in forensic science due to its ability to capture detailed spectral information from objects. The technology works by collecting and processing information from across the electromagnetic spectrum. Unlike traditional imaging, which captures pictures in primary colors (red, green, and blue), HSI captures images in a wide range of wavelengths from the visible light to near-infrared, providing a unique spectral signature for each material.

Applications of HSI in Forensic Blood Analysis

The applications of hyperspectral imaging in forensic blood analysis are vast and varied. One primary application is enhancing the visualization of bloodstains at crime scenes, especially on complex backgrounds or in low visibility conditions. HSI can differentiate blood from other substances with similar visual characteristics, reducing the likelihood of false positives in blood detection.

HSI is also used in aging bloodstains, which can be crucial in reconstructing events. By analyzing the spectral changes that occur as bloodstains age, forensic scientists can estimate the time since the blood was deposited. This can help in creating timelines of criminal activity, which are often critical in investigations.

Furthermore, HSI can assist in distinguishing between human and animal blood, which is not always possible with traditional chemical tests. This capability is essential when animal interference is suspected at a crime scene or when non-human blood is present.

hyperspectral imaging offers a robust tool for blood identification and classification, overcoming many of the limitations faced by traditional forensic blood analysis methods. Its non-destructive, detailed spectral analysis capability makes it a valuable addition to the forensic scientist's toolkit, with promising applications in crime scene investigation and evidence analysis. HSI offers several applications in forensic science, especially in the analysis of bloodstains at crime scenes:

Substance Classification: HSI can distinguish blood from other substances that visually appear similar, such as red wine or rust. This distinction is crucial in crime scenes where different fluids are present, ensuring that investigators focus only on relevant evidence. Age Estimation of Bloodstains: Determining the age of a bloodstain can be critical in reconstructing the timeline of criminal activities. HSI can help estimate the age of a bloodstain by analyzing its spectral changes over time, which are influenced by environmental factors and the degradation of blood components. Origin of Bloodstains: HSI can assist in determining whether bloodstains originated from arterial spurts, impact spatters, or transfer patterns, each of which can tell a different story about the events that occurred at the crime scene. Detection on Colored Backgrounds: Bloodstains on dark or multicolored backgrounds can be challenging to detect with the naked eye or even with traditional imaging techniques. HSI's capability to capture information beyond the visible spectrum allows it to detect bloodstains that are otherwise invisible, making it an invaluable tool in forensic examinations. Advantages Over Traditional Methods

The main advantage of HSI over traditional methods is its non-destructive nature. Unlike chemical tests that may alter the evidence, HSI preserves the integrity of bloodstains, allowing for repeated testing and reducing the risk of contaminating or destroying critical DNA evidence. Additionally, HSI provides quantitative data that can be critical in forensic analysis. The detailed spectral information captured by HSI enables forensic experts to conduct a more thorough and accurate analysis of bloodstains, leading to more reliable results in forensic investigations.

Challenges and Future Directions

Despite its advantages, the integration of HSI into routine forensic practice faces several challenges. The primary obstacle is the cost and complexity of hyperspectral cameras and the need for specialized training for forensic personnel. Moreover, the development of standardized protocols for the interpretation of HSI data in forensic contexts is still ongoing.
As technology advances, it is expected that HSI will become more accessible and cost-effective, making it a standard tool in the forensic scientist's toolkit. Researchers continue to refine the technology and develop new algorithms to improve the accuracy and efficiency of HSI in bloodstain analysis. The future of forensic science lies in embracing these advanced technologies, which hold the promise of providing clearer insights into criminal activities and contributing to the delivery of justice. HSI can differentiate substances based on their spectral signature, making it an effective tool for identifying and classifying bloodstains at a crime scene. Unlike traditional chemical methods, HSI is non-invasive and does not require direct contact with the bloodstain, thereby preserving the integrity
Our main target is to create a way to definitively verify that a stain is truly made up of blood. Visually bloodstains are similar with other substances, in color and appearance. This similarity complicates the differentiation process. Identifying genuine bloodstains for DNA testing is crucial in forensic investigations to avoid wasting time and resources on false positives, such as stains that may appear brown or similar to blood but are not actually blood. Dried bloodstains undergo various transformations as they age, resulting in alterations in color, texture. The identification of dried blood has emerged as an intriguing challenge in forensic science[8].
To estimate the depth of wound can be examined by the the spectral components of blood. The main key componete of blood is Hemoglobin derivatives, namely methemoglobin (metHB) and oxyhemoglobin (oxyHb). The distinctive spectral peaks of metHB and oxyHb in the VIS range spectra enable their identification and differentiation from other substances[9]. This is very important to understand how these entities behave when confronted with images that exhibit variations in both spatial and spectral features. Additionally, there is a phenomenon known as time-induced decay that affects bloodstains when they are exposed to environmental elements over a period of time. It offers valuable insights into the timeline of events at crime scenes

and aiding forensic investigations in reconstructing the sequence of events[9]. Furthermore, there exists a phenomenon called time-induced decay, which impacts bloodstains as they are subjected to environmental conditions over time. This phenomenon provides significant clues about the sequence of events at crime scenes, assisting forensic investigations in reconstructing timelines [8].

Our work focuses on employing various deep learning architectures to address specific questions, with a specific focus on forensic applications. For our work, we use a publicly available HSI dataset that ensures transparency and accessibility [10]. Due to the HSI dataset's characteristics of having high spectral but low spatial information, conventional 1-D and 2-D Convolutional Neural Networks (CNNs) are not appropriate for this task. These networks would only handle spectral data, neglecting spatial information. To overcome this limitation, 3D CNN is more suitable. These models process data across three dimensions concurrently, allowing for the effective learning of hierarchical features. This approach need less parameters than 1D, 2D CNN and minimizing the information loss.
Instead of the commonly used ReLU function, the Mish activation function is used here to enhance feature extraction and learning capabilities. There are some special properties like non monotonic function, possess self-regularization properties, vanishing gradient problem which makes it better than relu activation functions.

As HSI dataset contains high spectral and low spatial information, so traditional 1-D and 2-D Convolutional Neural Networks are not suitabe here . It will lose the spatial information but only process the spectral information. For this,3D CNN is used . By processing data across three dimensions simultaneously, 3D CNNs can effectively learn hierarchical features, reducing information loss and potentially requiring fewer parameters compared to stacking multiple 2D or 1D layers.

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less parameters than 1D, 2D CNN and minimizing the information loss.
The rest of the paper is structured as follows. Section II discussed state-of-the-art works proposed in the domain of forensic science. Section III presents the methodology used in this work. Section IV provides a detailed description of the experimental dataset, results, and discussion on obtained results. Finally, Section V concludes the paper with possible future research directions.

1.3 Overview

In forensic science, the classification of bloodstains at crime scenes plays a crucial role in the investigative process, helping to reconstruct events and identify perpetrators. Traditional methods of forensic analysis rely on visual inspection and chemical tests which can be subjective and limited in accuracy. The introduction of hyperspectral imaging in this field has been transformative. Unlike conventional imaging that captures only three bands (red, green, and blue), hyperspectral imaging captures images across a vast array of contiguous spectral bands. This capability allows for the capture of a wealth of spectral and spatial information from a scene, significantly more than what the human eye or standard cameras can perceive. This advanced imaging technique can differentiate substances based on their spectral signatures with high precision, making it invaluable for analyzing bloodstain patterns where such details can pinpoint the type of blood and its origin. The detailed information garnered includes not only the identification but also the characterization of bloodstains, considering factors like the age of the blood and potentially the diet or medication of the person involved, which can influence the spectral properties of the blood. This extensive detail offers forensic experts new avenues to gather evidence, providing clearer insights into crime scenes, which aids in enhancing the accuracy of forensic investigations.

1.4 Motivation

The development of an efficient and accurate method for classifying bloodstains in forensic analysis is motivated by the need to overcome the limitations of existing forensic methods. Current techniques often struggle with issues such as the degradation of biological samples, the influence of environmental factors on the samples, and the limited range of detectable information, which can lead to inaccuracies in the analysis. The objective of this research is to leverage hyperspectral imaging coupled with optimized 3D Convolutional Neural Networks (CNNs) to fully exploit both spectral and spatial information from bloodstains. This approach aims to significantly enhance the accuracy of bloodstain analysis, reduce the likelihood of human error, and provide a reproducible, objective method that can be standard across forensic laboratories. By improving the resolution at which forensic scientists can analyze bloodstains, this research hopes to contribute to more precise and scientifically sound investigations. Furthermore, the adoption of advanced image processing techniques, like dimensionality reduction through PCA, aims to manage the vast data more efficiently, improving processing times and reducing computational loads, which are critical for practical forensic applications.

1.5 Objective of the Thesis

The thesis presents a focused study on enhancing the detection and classification of bloodstains at crime scenes using advanced imaging techniques and deep learning models. Here are the main objectives outlined in the thesis, each discussed in detail:

1.5.1 Enhancement of Crime Scene Analysis

Bloodstain detection is a cornerstone of forensic science, often providing pivotal evidence that can elucidate the events at a crime scene. The primary objective of this thesis is to refine the process of analyzing crime scenes by employing advanced bloodstain detection techniques. Traditional methods, while effective, can be time-consuming and may not always deliver the needed granularity of detail quickly. By introducing an optimized 3D Convolutional Neural Network (CNN) model, which incorporates the capabilities of Hyperspectral Imaging, the thesis aims to provide a more nuanced understanding of bloodstain composition and distribution. This method allows forensic investigators to more accurately reconstruct the sequence of events, understand the mechanics of the crime, and establish timelines, ultimately leading to more effective and efficient resolution of criminal cases. The ability to rapidly and accurately process crime scene data not only expedites investigations but also enhances the reliability of the evidence gathered, thereby supporting the judicial process.

1.5.2 Introduction of Hyperspectral Imaging in Forensic Science

Hyperspectral Imaging (HSI) is a technology that captures and processes information from across the electromagnetic spectrum. Unlike traditional imaging techniques that capture images in three basic color components (red, green, and blue), HSI can capture images in many wavelengths simultaneously, providing a much more detailed spectral signature of the scene. In the context of forensic science, this capability can be particularly useful for identifying subtle differences in bloodstains that could be overlooked by standard methods. This thesis explores the integration of HSI with 3D CNN models to create a powerful tool for bloodstain detection and classification. The detailed spectral data obtained from HSI allows the neural network to learn and identify characteristics of bloodstains with a high degree of accuracy, which can significantly enhance the identification of blood origin, such as from different individuals, or discerning bloodstains from other substances.

1.5.3 Development and Optimization of a 3D CNN Model

Developing an effective 3D CNN model involves creating a deep learning architecture that can process and analyze the voluminous data provided by HSI. The objective here is to optimize this model to maximize its accuracy and efficiency in classifying bloodstains. The optimization process involves tweaking the network architecture, adjusting layers, and testing various activation functions to find the most effective combination for the task. This thesis introduces an optimized 3D CNN with a Mish activation function, known for its ability to maintain a healthy gradient flow, which is crucial in training deep neural networks effectively. By optimizing the model, the thesis aims to improve the detection and classification performance, making it robust against various challenges encountered in forensic analysis.

1.5.4 Incorporation of the Mish Activation Function

Activation functions in neural networks are critical as they determine how neurons get activated and pass information within the network. The Mish activation function is utilized in this thesis due to its mathematical properties that help in reducing the likelihood of vanishing gradients—a common problem in training deep neural networks. This function helps in maintaining the smooth flow of gradients throughout the training process, which in turn enhances the learning and generalization capabilities of the network. This choice is justified by the improved performance metrics of the model, especially in a complex classification task like bloodstain analysis where precision is crucial.

1.5.5 Comparison with Existing Models

A significant part of this thesis is dedicated to comparing the performance of the optimized 3D CNN model against existing models. This comparison not only illustrates the improvements in accuracy—from 95% in existing 3D CNNs to 97% in the optimized model—but also highlights the efficiency in terms of computational resources. The optimized model uses fewer parameters (a reduction from 291,895 to 125,943), which indicates a more efficient model that can perform faster without compromising on accuracy. This comparison is vital for establishing the efficacy of the new model and its potential to replace or supplement current methods in forensic science.

1.5.6 Resource Efficiency

In forensic analysis, time and computational resources are of the essence. The objective of enhancing resource efficiency is addressed by reducing the number of parameters in the 3D CNN model, thereby not only simplifying the computational process but also speeding it up. This efficiency does not come at the cost of performance. On the contrary, the model maintains a high accuracy level, making it a viable tool for quick and reliable bloodstain analysis. This improvement is particularly significant in a practical forensic setting, where quick turnaround times can be critical to the success of an investigation.

1.5.7 Achievement of High Accuracy

The optimized 3D CNN model achieves a remarkable accuracy of 97%, which surpasses the performance of previous models. This high level of accuracy is crucial for forensic applications where the stakes are high and the cost of errors can be severe. The model's ability to accurately classify bloodstains ensures that forensic analysts can rely on the data to make informed decisions about the crime scene. This accuracy is particularly significant in the context of legal proceedings where forensic evidence must meet high standards of reliability.

1.5.8 Implications for Forensic Investigations

The improved accuracy and efficiency of the bloodstain detection process have direct implications for forensic investigations. Faster and more accurate bloodstain analysis can lead to quicker resolutions of cases, potentially increasing the chances of solving crimes. It can also enhance the credibility of forensic evidence in court, thereby supporting the judicial process. This thesis underscores the practical benefits of integrating advanced technological tools into forensic science, which can ultimately lead to more effective law enforcement and justice delivery.

1.5.9 Future Scope and Applications

While this thesis focuses on bloodstain detection, the methodologies developed have broader applications in forensic science. The future scope of this research could extend to other types of evidence analysis, such as saliva, semen, or other biological substances. Moreover, the integration of 3D CNN models with other imaging technologies could open new avenues for forensic investigations, offering more comprehensive tools for crime scene analysis.

1.5.10 Contribution to Forensic Science Knowledge Base

By pushing the boundaries of what is technically feasible in forensic science, this thesis contributes significantly to the field's knowledge base. It not only introduces new techniques and methodologies but also provides empirical evidence of their effectiveness. This contribution is crucial for ongoing research and development in forensic technologies, helping to build a stronger, more scientifically robust foundation for forensic investigations.

Each of these objectives is aligned with the overarching goal of enhancing the tools available to forensic scientists, thereby enabling more accurate and efficient investigations. This thesis not only contributes to the academic field but also has practical implications that can improve the effectiveness of law enforcement agencies in solving crimes.

1.6 Conclusion

In this chapter, we were provided with an overview of the upcoming study and a glimpse into the work that lies ahead. The discussion included insights into the inspiration, objectives, and research challenges that will be further elaborated in subsequent chapters.

Chapter 2

Background 3D Convolutional Neural Network

2.1 Introduction

3D CNNs are well-suited for processing hyperspectral imaging data which encompasses multiple spectral bands, providing a rich source of data that traditional 2D CNNs cannot handle effectively. By integrating the depth dimension, 3D CNNs allow simultaneous analysis of spatial and spectral features, crucial for identifying complex patterns in high-dimensional data.

2.1.1 Overview of 3D CNN Architecture

Handling High-Dimensional Data

Hyperspectral images capture information across a broad spectral range, resulting in high-dimensional datasets. Traditional imaging techniques and 2D CNNs often fall short in managing the depth of information provided by these images. 3D CNNs address this by processing the data in three dimensions (width, height, depth), which allows them to capture the complex interactions between spatial and spectral features effectively.

Enhanced Feature Extraction

The architecture of a 3D CNN enables it to extract volumetric features that are essential for the detailed analysis required in forensic investigations. These features include the textural and chemical properties of bloodstains, which can significantly differ from other substances even if they are visually similar.

Improved Accuracy in Classification

The application of 3D CNNs in this thesis has shown to achieve higher accuracy levels, with a reported 97

Efficiency and Resource Management

The optimized 3D CNN model described in this thesis uses significantly fewer parameters compared to traditional models. This efficiency in the model architecture not only reduces computational demands but also enhances processing speeds, making it suitable for real-time analysis applications in forensic science.

Adaptation to Forensic Needs

The specific design of the 3D CNN, including its layer architecture and activation functions, addresses the unique challenges in forensic analysis. This model is tailored to differentiate between complex biological and non-biological substances in crime scene investigations, ensuring high reliability and validity of the forensic analysis.

2.1.2 Specific Architectural Features

Mish Activation Function

The Mish activation function is utilized in this model to maintain smooth and healthy gradient flow during the training phase, which can help in preventing common issues like vanishing gradients. This function supports the model in learning more effectively from the complex datasets typical of forensic applications.

Dimensionality Reduction via PCA

Before processing by the 3D CNN, hyperspectral data is subjected to dimensionality reduction using PCA. This method highlights significant features while minimizing noise, which simplifies the dataset and enhances the model's focus on relevant features for bloodstain detection.

Optimized Layer Design

The convolutional layers of the 3D CNN are specifically designed to process three-dimensional data, which allows the model to effectively learn both spatial and spectral features. This optimization is crucial for handling the detailed information provided by hyperspectral imaging.

2.1.3 Comparison with Other CNN Models

This thesis includes a comparative analysis of the 3D CNN with traditional 2D CNNs and hybrid models, demonstrating its superior performance. This comparison underscores the advantages of using a 3D approach in terms of both accuracy and computational efficiency, particularly in complex forensic applications.

2.1.4 Impact on Forensic Science

By implementing an optimized 3D CNN model for bloodstain detection, this research significantly contributes to forensic science, providing a robust analytical tool that enhances the accuracy and efficiency of crime scene investigations. This advancement could transform forensic methodologies, leading to faster and more reliable analysis, which is crucial for the judicial process.

2.2 Conclusion

This thesis has demonstrated the effectiveness of an optimized 3D Convolutional Neural Network (CNN) model in the advanced forensic analysis of bloodstains using hyperspectral imaging. The adoption of this technology marks a significant improvement over traditional forensic methods, offering higher accuracy and efficiency in bloodstain detection and classification.

2.2.1 Summary of Findings

The optimized 3D CNN model addressed several limitations of previous techniques by effectively integrating spatial and spectral data, thus enabling more accurate classification of bloodstains with a remarkable accuracy of 97%. This model has proven superior to existing 2D and hybrid CNN models, not only in terms of accuracy but also in computational efficiency, as evidenced by the reduction of model parameters from 291,895 to 125,943.

2.2.2 Contributions to Forensic Science

The research has contributed significantly to forensic science by providing a robust analytical tool that enhances the precision and speed of bloodstain analysis. This improvement is crucial for the timely and effective resolution of criminal cases, aiding forensic experts in reconstructing crime scenes with greater detail and accuracy. Additionally, the use of the Mish activation function and PCA for dimensionality reduction has set a new standard for the application of machine learning techniques in forensic investigations.

2.2.3 Future Directions

While the current model offers substantial benefits, future research could explore the integration of additional datasets and the refinement of the network architecture to further enhance its accuracy and efficiency. Exploring the application of similar 3D CNN architectures in other areas of forensic science, such as the analysis of other bodily fluids or trace evidence, could provide broader implications for the field.

In conclusion, the successful implementation of the 3D CNN model represents a forward leap in forensic science technology. It not only enhances the capabilities of forensic professionals but also supports the broader goals of the criminal justice system by improving the reliability and speed of crime scene analysis. The findings of this thesis encourage ongoing innovation and adaptation of advanced computational models in forensic applications, promising a future where forensic science is more accurate, efficient, and aligned with technological advancements.

Chapter 3

Literature Review

3.1 Introduction

Hyperspectral imaging is a novel imaging technique gaining momentum in medical realms, especially for disease diagnosis and providing visual guidance during surgical procedures . Hyperspectral imaging (HSI) is a method used in forensic science because it is quick, doesn't cause any damage, and doesn't require physical contact with the evidence .

3.2 Related Works

Forensic labs employ different approaches to identify bloodstains. Presumptive tests are initial assessments that provide an indication but may not confirm definitively.[9] The Kastle-Meyer (KM) test is specifically highlighted as one of the presumptive tests employed in forensic labs.The specificity of the KM reaction compared to benzidine in identifying stains from various sources such as bodily fluids, fruits, vegetables, and chemicals. The KM reaction exhibits higher specificity in contrast to benzidine [11].

Besides,Luminol is highly regarded and widely recognized as one of the most significant assays (tests or analyses) in forensic science.Luminol's effectiveness can be influenced by environmental conditions like ambient light, humidity, and temperature can impact the sensitivity and reliability of the test. This work compares different luminol formulations that focus on their luminescence and longevity [10]. Advancements in laser technology and light detectors have significantly enhanced spectroscopic methods for characterizing molecules. These improvements have opened up new opportunities for on-site, conclusive identification of body fluids at crime scenario [12]. In the paper [13], they analyzed reflectance spectra from 35 stains that were not blood and 40 stains that were bloodstains, all of which were on white cotton fabric. All the models that were tested demonstrated an ability to accurately identify deposited stains as blood, with a maximum accuracy of 94% and a minimum accuracy of 81% [14] . The analysis resulted in correctly classifying 92% of the spectra during a leave-one-out cross-validation (LOOCV) process, where each spectrum was temporarily excluded from the model's training set and then tested against the model[15], .

The identification of blood traces is facilitated by noncontact techniques, primarily due to challenges in maintaining temperature and humidity with traditional methods. Researchers turned to Hyperspectral Imaging (HSI) as it allows blood identification without contact that reduce the risk of destruction . The advantages include rapid data collection, no need for sample preparation and reduced workload in laboratories [16].
The current methods for detecting and identifying blood stains, involving visual examination and presumptive tests, have limitations such as false positives and potential interference with DNA tests. They introduced a new way of using hyperspectral imaging, specifically in the visible wavelength range, to detect and confirm blood stains on different colored surfaces without touching or damaging them. The method is capable of distinguishing between blood stains and nine other substances that are red in color, as well as identifying blood approximately from 40 reddish stains [17]. The paper [18] introduced an Active Learning (AL) pipeline aimed at addressing the challenge of sample selection in hyperspectral image (HSI) classification. They utilized deep convolution networks with a hybrid dilated residual approach, aiming to improve HSI classification performance by adaptively selecting spectral bands and overcoming limitations associated with manually crafted selections. In this paper [19], they improved the robustness of hyperspectral image classification by investigating the application of Deep Support Vector Machine (DSVM) with various kernel functions. The challenge of stain detection is particularly in confirming whether in a crime scene a stain is a bloodstain or not.

To overcome this difficulty, the confirmation of bloodstains is difficult, especially considering the implications of false positives.Deoxyribonucleic Acid (DNA) analysis is a powerful method for identifying suspects, but this approach is very expensive ,more costly and time consuming

[20] . Consequently, if a false positive occurs, such as with a stain that appears similar to blood but is not, it waste not only significant time but also waste resources [21]. SO,it is important to develop accurate and efficient methods for confirming bloodstains at crime scenes to avoid potential false positives and the associated costs and resources[22].

3.3 Conclusion

As we say earlier that DNA analysis is need more money and more costly and more time needed . So we need to introduce a more efficient model that likely consumes less computational resources, leading to potential cost savings in hardware and energy consumption. However, most of these models fall short of achieving an accuracy above 95%. In response to this limitation, I have developed and implemented my proposed methodology to address the issue.

Chapter 4

Dataset

4.1 Introduction

Hyperspectral image data is like a three-dimensional cube where each point represents a pixel in an image.It contains information about both the color and location of each pixel.This cube is made up of width, height and depth, where depth represents the number of different colors or spectral bands captured in the image. Each pixel is labeled with a vector indicating its category, with similarities and differences existing within each category. The image may contain overlapping categories, making it challenging to distinguish them accurately.

4.2 Dataset Description

The dataset is called "Hyperblood" Hyperspectral-based Bloodstain dataset. This dataset has different types of substances i.e., blood and blood-like compounds, for instance, ketchup, artificial blood, beetroot juice, poster paint, tomato concentrate, acrylic paint, uncertain blood.[1]
Source : www.kaggle.com

- Dataset contains: 14 hyperspectral images (ENVI format)
- Image size: 519×696 pixels (each pixel contains 113 bands)
- Number of Classes: 7
- Number of Dimensions: 15
- Shape of HSI: $(519, 696, 113)$

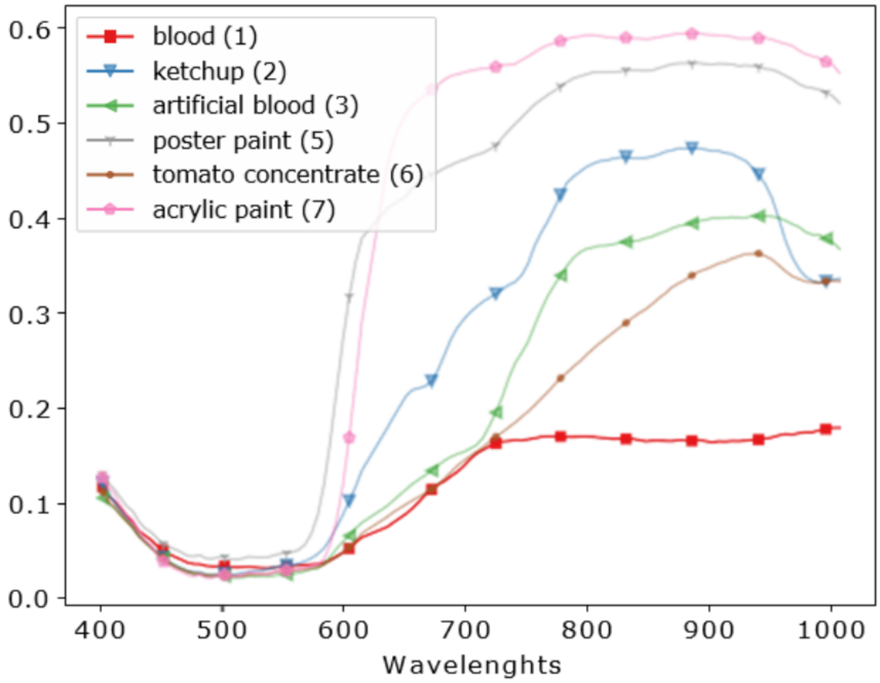


Figure 4.1: Hyperblood Dataset

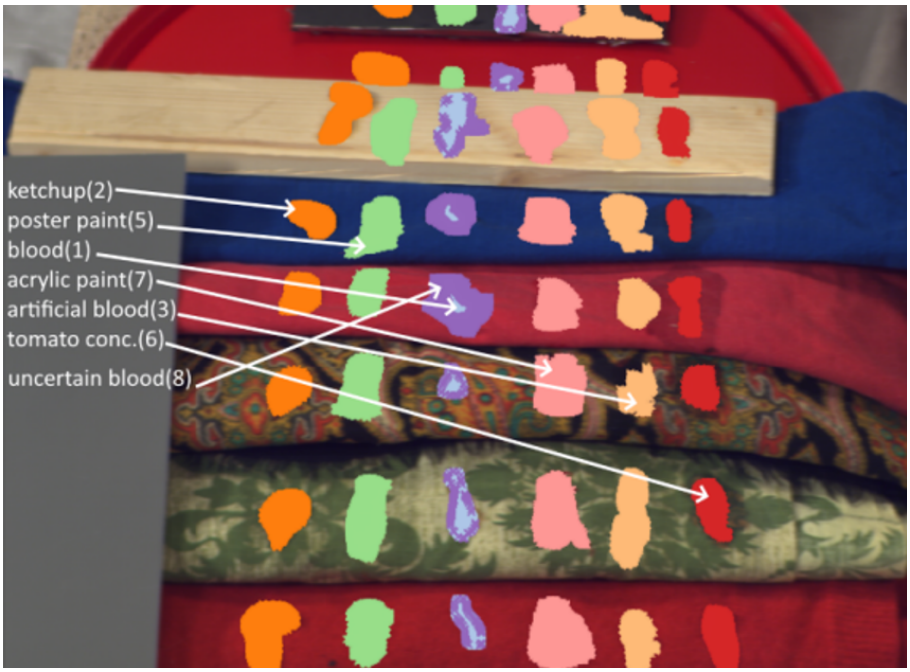


Figure 4.2: Dataset with Class

- Shape of GT: $(519, 696)$
- Name of Classes: [0, 1, 2, 3, 4, 5, 6, 7]
- Source: `www.kaggle.com`

4.3 Conclusion

This chapter discusses the elements crucial for the suggested method in the machine learning-based architecture, including dataset, data pre-processing, feature reduction methods, machine learning models-based framework, training and testing set, and hyperparameter tuning with GridSearch.

Chapter 5

Proposed Methodology & Implementation

5.1 Introduction

Employing various deep learning architectures to address specific ques- tions, with a specific focus on forensic applications. For our work, we use a publicly available HSI dataset that ensures transparency and accessibility . Due to the HSI dataset's character- istics of having high spectral but low spatial information, conventional 1-D and 2-D Convolu- tional Neural Networks (CNNs) are not appropriate for this task. These networks would only handle spectral data, neglecting spatial information. To overcome this limitation, 3D CNN is more suitable. These models process data across three dimensions concurrently, allowing for the effective learning of hierarchical features. This approach need less parameters than 1D, 2D CNN and minimizing the information loss. Instead of the commonly used ReLU function, the Mish activation function is used here to en- hance feature extraction and learning capabilities. There are some special properties like non monotonic function, possess self-regularization properties, vanishing gradient problem which makes it better than relu activation functions. As HSI dataset contains high spectral and low spatial information, so traditional 1-D and 2- D Convolutional Neural Networks are not suitabe here . It will lose the spatial information but 2 only process the spectral information. For this,3D CNN is used . By processing data across three dimensions simultaneously, 3D CNNs can effectively learn hierarchical features, reduc- ing information loss and potentially requiring fewer parameters compared to stacking multiple 2D or 1D layers

5.2 Methodology

Hyperspectral image data is like a three-dimensional cube where each point represents a pixel in an image.It contains information about both the color and location of each pixel. This cube is made up of width, height and depth, where depth represents the number of different colors or spectral bands captured in the image. Each pixel is labeled with a vector in- dicating its category, with similarities and differences existing within each category. The image may contain overlapping cat- egories, making it challenging to distinguish them accurately. To simplify this complex data, preprocessing is done using Principal Component Analysis (PCA) , reduced the number of colors while preserving important spatial information, thereby aiding in analysis and interpretation.

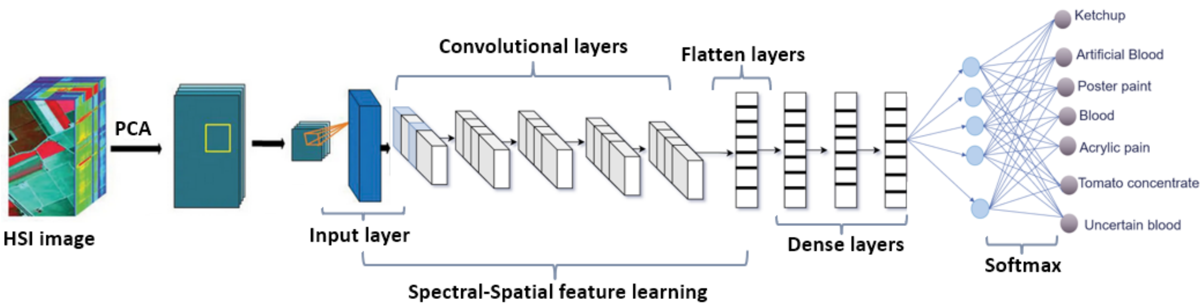


Figure 5.1: Proposed 3D CNN (Kernel size =3 × 3 × 7, $3D_{\text{input}} = 9, 9, 15, 1$)

To effectively process hyperspectral imaging (HSI) data for image classification, a three-dimensional Convolutional Neural Network (3D CNN) is employed, utilizing its unique structure tailored for analyzing spatial-spectral information. First of all, the HSI cube is divided into small overlapping 3D patches to analyze individual pixels closely. These patches enabling localized analysis centered around individual pixels. These patches are then fed into the 3D CNN, which com- prises multiple layers of 3D convolutional operations. Unlike traditional 2D CNNs, which analyze spatial information only, the 3D CNN operates on both spatial and spectral dimensions simultaneously, enabling it to capture complex spatial-spectral patterns inherent in HSI data. The structure of the 3D CNN includes multiple layers of 3D convolutional kernels followed by activation functions to introduce nonlinearity. In this image classification algorithms, the process begins by dissecting the HSI cube into smaller overlapping 3D-patches. These patches are meticulously crafted, with their truth labels discerned based on the central pixel's label. Following this initial step, neighbor patches N p □ Rw×w×B are crafted, employing a spatial window of w ×w centered around specific spatial coordinates (x, y) . Each of these neighbor patches, denoted as n patches, covers a designated area, spanning the width and height dimensions of the HSI cube. This coverage ranges from $(x - w + 1/2)$ to $(x + w - 1/2)$ and $(y - w + 1/2)$ to $(y + w - 1/2)$. In 3D CNN , 3D convolutional procedures and 3D kernel extracts spatial and spectral information from HSI cube. Instead of the commonly used ReLU function, the Mish activation function is used here to enhance feature extraction and learning capabilities. This function introduces smoothness and better gradients compared to ReLU, thereby improving the learning process. The 3D CNN architecture, augmented with the Mish activation function, effectively processes HSI data, extracting discriminative spatial-spectral features crucial for accurate image classification tasks. The Mish activation function is defined as $f(x) = x \cdot \tanh(\ln(1 + ex))$ 3×3 karnel size is used . Table-1 shows other details . The proposed model contains 125043 trainable parameters.Here ”Adam” optimizer is used for optimizing the softmax function. For train and validate the 3D CNN model 10 epochs are used.

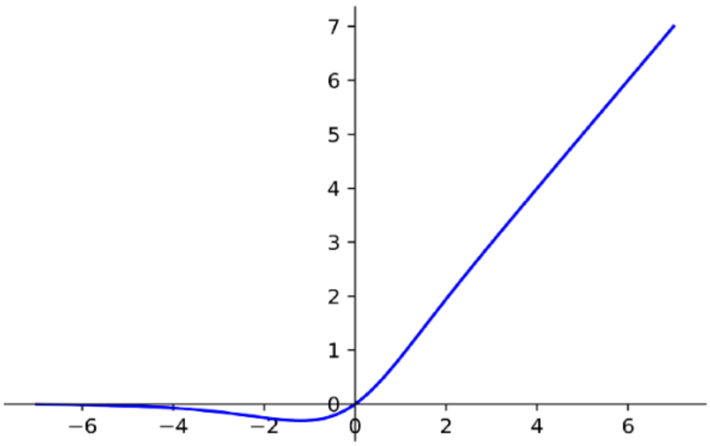


Figure 5.2: Mish Activation Function

The preprocessing of such intricate data typically involves the application of Principal Component Analysis (PCA). PCA helps reduce the spectral dimensionality, simplifying the spectral information while preserving crucial spatial details, thereby facilitating easier analysis and interpretation of the data.

A prominent technique employed in the analysis of HSI data is the use of a 3D Convolutional Neural Network (3D CNN). This methodology leverages the unique structure of 3D CNNs, which are particularly suited for handling spatial-spectral data integration. The first step in this process involves segmenting the HSI cube into smaller, overlapping 3D patches. These patches

Table 5.1: Proposed 3D CNN architecture model summary (Window size is 9×9)

Layer (type)	**Output Shape**	**Param #**
input_1 (InputLayer)	[(None, 9, 9, 15, 1)]	0
conv3d_1 (Conv3D)	(None, 7, 7, 9, 8)	512
conv3d_2 (Conv3D)	(None, 5, 5, 5, 16)	5776
conv3d_3 (Conv3D)	(None, 3, 3, 3, 32)	13856
conv3d_4 (Conv3D)	(None, 1, 1, 1, 64)	55360
flatten_1 (Flatten)	(None, 64)	0
dense_1 (Dense)	(None, 256)	16640
dense_2 (Dense)	(None, 128)	32896
dense_3 (Dense)	(None, 7)	903
Total params: 125943 (491.96 KB)		
Trainable params: 125943 (491.96 KB)		
Non-trainable params: 0 (0.00 Byte)		

allow for localized examination around individual pixels, enhancing the focus on minute details and variations within the data.

5.2.1 Optimized 3D Convolution Neural Network

In hyperspectral image (HSI) analysis, 3D convolution is a critical technique for extracting spatial and spectral features. This process involves the use of a three-dimensional kernel that moves across the input data in all three dimensions (spatial width, spatial height, and spectral depth), performing a dot product at each position. The output is a new volume that represents feature activation across both spatial and spectral domains. The equation for 3D convolution is defined as follows:

$$D_{u,v}^{i,j,k} = \mathrm{ReLU}\left(\sum_{\rho=1}^{s_{u-1}} \sum_{\pi=-\gamma}^{\gamma} \sum_{\lambda=-\eta}^{\eta} \sum_{\omega=-\epsilon}^{\epsilon} Q_{\pi,\lambda,\omega}^{u,v,\rho} \times D_{(i+\pi)(j+\lambda)(k+\omega)}^{(u-1),\rho} + b_{u,v}\right) \quad (5.1)$$

Detailed Explanation:

- $D_{u,v}^{i,j,k}$: Represents the output feature map at the position (i, j, k) within the volume processed by the u-th layer's v-th feature map.

- **ReLU (Rectified Linear Unit)**: This is a non-linear activation function used to introduce non-linearity into the network, helping it to learn more complex patterns. The ReLU function outputs zero for any negative input and returns the input as is for any positive input.

- s_{u-1}: Number of feature maps in the layer preceding the current one, indicating the depth of the input volume that the kernel interacts with.

- $Q^{u,v,\rho}_{\pi,\lambda,\omega}$: The kernel or filter weights specific to the ρ-th feature map of the previous layer $(u-1)$, indexed by π, λ, ω which traverse width, height, and depth respectively.

- $D^{(u-1),\rho}_{(i+\pi)(j+\lambda)(k+\omega)}$: The input feature map value from the previous layer at a specific offset defined by π, λ, ω, essential for capturing local feature dependencies across different dimensions.

- $b_{u,v}$: The bias term for the v-th feature map in the u-th layer, used to adjust the output along with the weighted sum of the inputs.

Following 3D convolutional layers, 2D convolutions are applied, primarily focusing on enhancing spatial feature representations while reducing the spectral dimension. This step is crucial for tasks like image classification where spatial relationships are significant. The equation for 2D convolution is:

$$D^{i,j}_{u,v} = \text{ReLU}\left(\sum_{\rho=1}^{s_{u-1}} \sum_{\pi=-\gamma}^{\gamma} \sum_{\lambda=-\eta}^{\eta} Q^{u,v,\rho}_{\pi,\lambda} \times D^{(u-1),\rho}_{(i+\pi)(j+\lambda)} + b_{u,v}\right) \tag{5.2}$$

Detailed Explanation:

- $D^{i,j}_{u,v}$: The output feature at position (i, j) in the u-th layer and v-th feature map, representing a 2D spatial map.

- $Q^{u,v,\rho}_{\pi,\lambda}$: The weights of the 2D kernel impacting the v-th feature map of the u-th layer, operating on the ρ-th feature map from the previous layer. These weights slide over the width (π) and height (λ) of the input map.

- $D^{(u-1),\rho}_{(i+\pi)(j+\lambda)}$: Refers to the value from the previous layer's feature map at the adjusted location, critical for integrating local spatial information into higher-level feature detection.

- The inclusion of ReLU and bias ($b_{u,v}$) follows similar principles as in 3D convolution, aimed at adjusting and activating the output feature map for further processing or classification tasks.

The structure of the 3D CNN is crafted to include multiple layers of 3D convolutional operations. Unlike traditional 2D CNNs, which primarily analyze spatial information, 3D CNNs process both spatial and spectral data simultaneously. This capability is crucial for capturing the complex spatial-spectral patterns inherent in HSI data. The layers in a 3D CNN consist of multiple 3D convolutional kernels, followed by activation functions such as the Mish function, which introduces nonlinearity into the model. The Mish activation function is particularly noted for its ability to provide smoother and more effective gradients than traditional functions like ReLU, enhancing the overall learning and feature extraction processes.

5.3 Experimental setup and Implementation

This data set is available online (www.kaggle.com) and experimented on an online platform Kaggle.com . Kaggle provides free access to NVIDIA TESLA P100 GPUs. Kag- gle offers a generous allocation of cold storage, providing users with 358.27 GB of storage space. Additionally, Kaggle generously allocates a substantial amount of Random Access Memory (RAM), providing users with 25 GB of memory to efficiently handle large datasets and complex computational tasks. This experiment is divided into three separate sets (Train/Validation/Test).These sets are Training (1690, 9, 9, 15, 1) Validation (1690, 9, 9, 15, 1) Test (30424, 9, 9, 15, 1) . The whole dataset is spilt into three ratio . Here Training : Validation : Test is 5% : 5% : 90% .For training purpose 5% is used and 5% is used for validation purpose and rest of the 90% is considered as test set .

5.4 Conclusion

This chapter discusses the elements crucial for the suggested method in the 3D CNN architecture, including dataset, data pre-processing, feature reduction methods, machine learning models-based framework, training and testing set.

Chapter 6

Result & Performance Analysis

6.1 Introduction

Before delving into the specifics of the paragraph, it is essential to understand the fundamentals of Convolutional Neural Networks (CNNs). CNNs are a class of deep neural networks, most commonly applied to analyzing visual imagery. They are known for their ability to automatically detect important features without any human supervision, using what are known as filters or kernels. The architecture of a CNN typically consists of several layers including convolutional layers, pooling layers, and fully connected layers that end in an output layer typically employing a softmax function for classification tasks.

Principle Component Analysis (PCA) to select the 15 most informative bands. PCA is a statistical technique used to emphasize variation and bring out strong patterns in a dataset. It's often used in exploratory data analysis and for making predictive models. It works by transforming the original variables into a new set of variables, which are linear combinations of the original variables. These new variables, or principal components, are orthogonal (as in, statistically independent) and are ordered so the first few retain most of the variation present in all of the original variables.

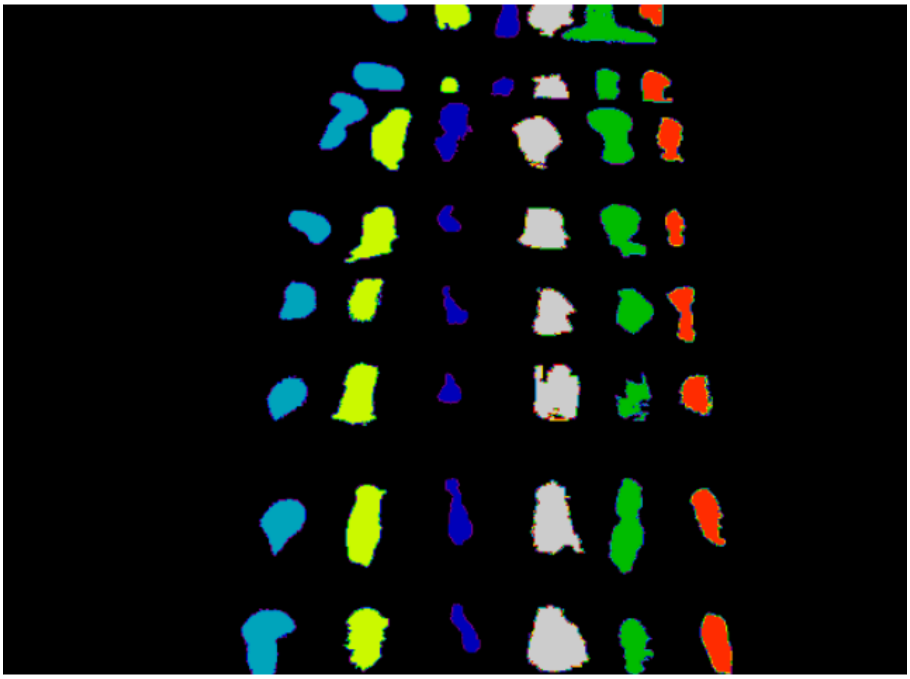
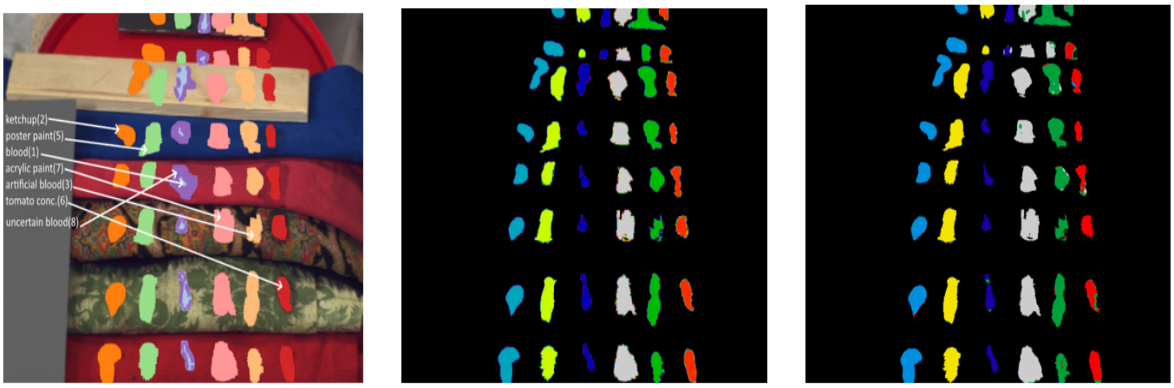


Figure 6.1: Original Ground truth

6.2 Result and Performance Analysis

15 most informative band is selected by using the principle component analysis (PCA) method. While training the model 0.001 learning rate is used. In comparison the proposed 3D CNN model's overall ac- curacy (OA) is higher than the traditional 3D CNN model. Before Optimizing the CNN model traditional ReLU activation function is used and after optimizing the 3D CNN model we use mish activation function and in output layers softmax function is used. Whole evaluation result curves are shown in Table-II. Here some comparison curve including confusion matrix, precision, recall and f1-score curve shown in Table-IV and igure 7 . The overall accuracy is increased from 95% to 97%.

3D CNNs extend the concept by not only processing width and height dimensions but also the depth dimension, making them suitable for interpreting volumes or sequences, such as video data or medical imaging scans. The specific improvements in the 3D CNN model discussed involve optimization changes, including a shift from a traditional Rectified Linear Unit (ReLU) activation function to the Mish activation function. The Mish function is a newer, non-monotonic function that may help in reducing issues like the vanishing gradient problem, which affects deep networks. Furthermore, softmax activation is used in the output layers, a standard choice for multi-class classification tasks as it converts the output to a probability distribution



a) Original image b) Ground truth c) Predicted ground truth

Figure 6.2: Original image, Ground truth and Predicted ground truth after 3D CNN

Table 6.1: Classification Results using Optimized 3D CNN Model

Class	**Precision**	**Recall**	**F1-Score**	**Support**
blood	0.99	0.96	0.97	2668
ketchup	1.00	0.98	0.99	5259
artificial blood	0.93	0.92	0.93	5774
poster paint	1.00	1.00	1.00	5963
tomato concentrate	0.89	0.93	0.91	3541
acrylic paint	0.98	0.98	0.98	7219
Accuracy	0.97			
Macro Avg	0.96	0.96	0.96	30424
Weighted Avg	0.97	0.97	0.97	30424

over predicted output classes.

The experiment setup outlined demonstrates the model's performance in classifying different substances, likely from image data given the context of a 3D CNN. Substances like blood, ketchup, and various types of paints are classified with high precision, recall, and F1-scores, indicating a robust model performance. Detailed results in terms of these metrics are presented in Table II, showing the effectiveness of the optimized model across various classes. Moreover, overall model accuracy improved from 95 It highlights improvements not only in accuracy but also in computational efficiency, as the number of parameters was substantially reduced. This

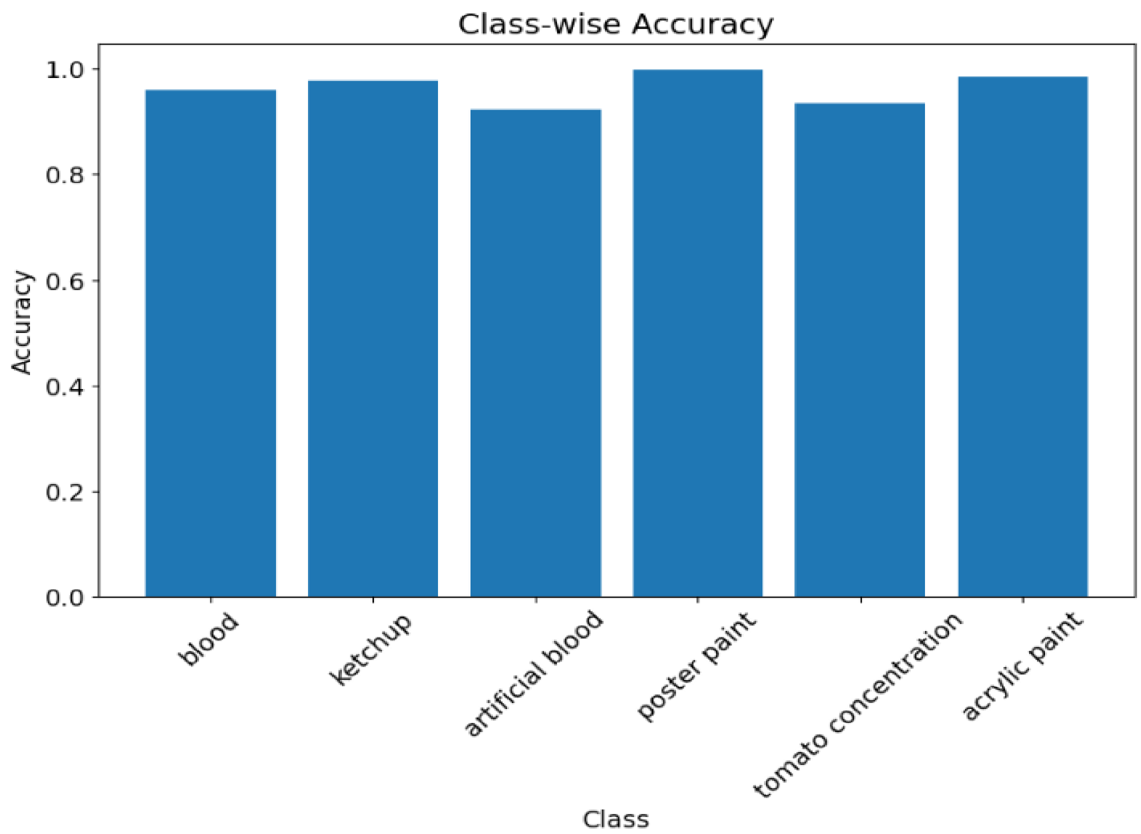
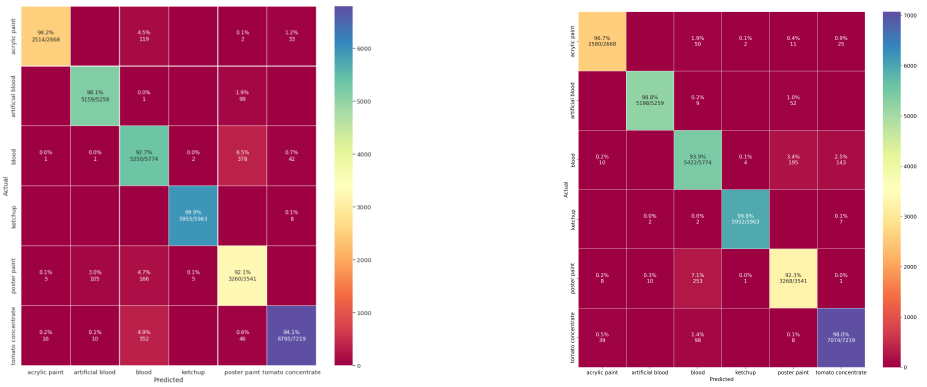


Figure 6.3: Class wise Accuracy

Table 6.2: Comparison of Precision, Recall, and F1-Score ("1" refer to 3D CNN and "2" refer to Optimized 3D CNN)

Class	**Pre1**	**Pre2**	**Re1**	**Re2**	**F1-Sc1**	**F1-Sc2**
blood	0.99	0.99	0.94	0.96	0.97	0.97
ketchup	0.98	1.00	0.98	0.98	0.98	0.99
artificial blood	0.89	0.93	0.93	0.92	0.91	0.93
poster paint	1.00	1.00	1.00	1.00	1.00	1.00
tomato concentrate	0.86	0.89	0.92	0.93	0.89	0.91
acrylic paint	0.99	0.98	0.94	0.98	0.96	0.98

reduction in model complexity without sacrificing accuracy is crucial in deploying models in real-world applications where computational resources and response times are often limited. Figures and tables (Table IV, Fig. 7) mentioned in the text likely provide visual insights into the model's performance across different classes and comparisons between the original and optimized models. These include confusion matrices and learning curves, essential tools for



(a) Confusion matrix of 3D CNN[8] (b) Confusion matrix of Optimized 3D CNN

Figure 6.4: Confusion matrix curve

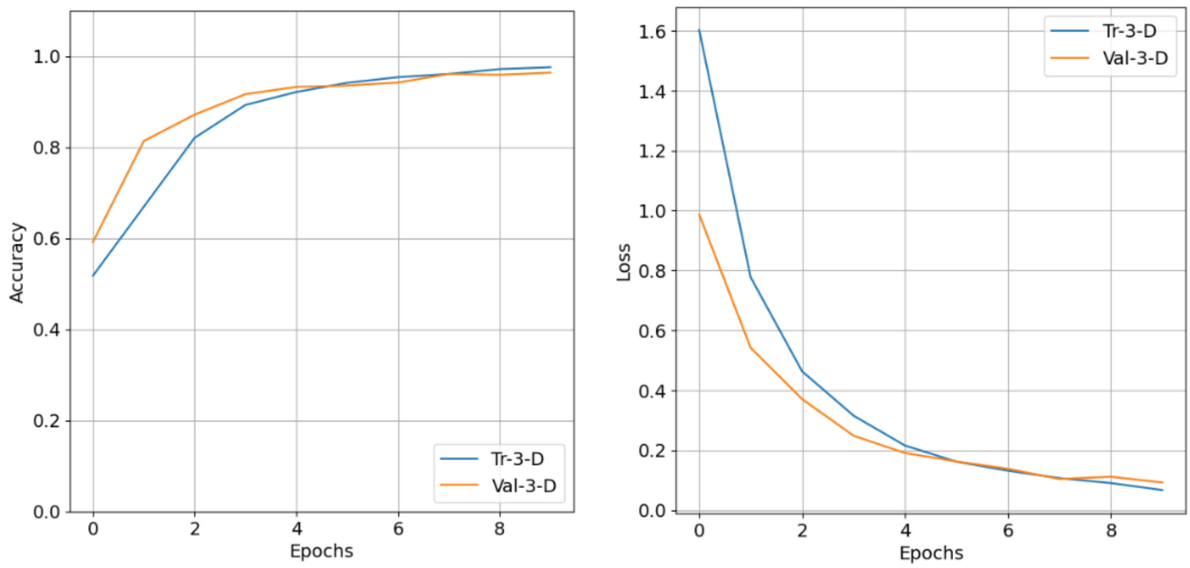


Figure 6.5: Learning curve of Optimized 3D CNN

understanding model behavior and identifying potential areas of misclassification.

Table 6.3: Classifier Performance

Classifiers	**Accuracy**	**Macro avg**	**Weighted avg**	**Parameter**
3D CNN	**0.95**	**0.95**	**0.95**	**291895**
Hybrid CNN	**0.96**	**0.97**	**0.96**	**291895**
Proposed 3D CNN	**0.97**	**0.96**	**0.97**	**125943**

Analysis of Model Performance

The following report provides a comparison of the performance metrics for two machine learning models: the standard 3D Convolutional Neural Network (CNN) and its optimized counterpart. These metrics are crucial for evaluating the effectiveness of each model in classifying different substances.

Analysis of Model Performance

The following sections delve into the comparative analysis of performance metrics between two convolutional neural network models. By examining precision, recall, and F1-scores, we gauge the efficacy of a standard 3D CNN and its optimized variant across a spectrum of classes.

Bar Charts Comparison

Figure 1.6 showcases a triad of bar charts, each of which articulates the disparity in precision, recall, and F1-scores for a set of categories. These categories represent various substances such as blood, ketchup, artificial blood, poster paint, tomato concentrate, and acrylic paint. In each chart, the performance metrics of the standard 3D CNN are color-coded in blue, whereas the metrics for the Optimized 3D CNN are depicted in orange. A pattern emerges from these visual representations, where the Optimized 3D CNN consistently equals or surpasses the performance of the standard model, marking an advance in its predictive capabilities.

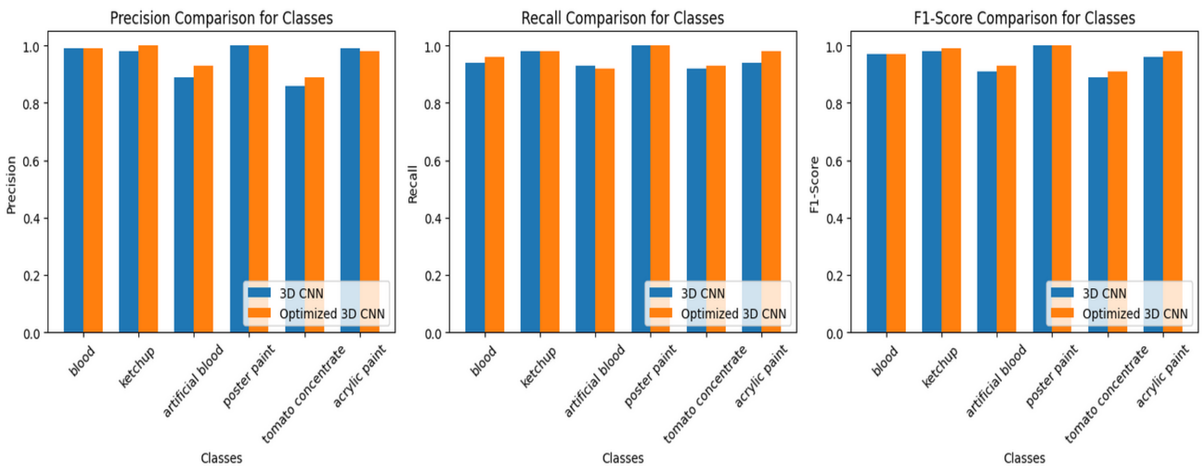


Figure 6.6: Recall Precision F1 Together Bar graph

Line Charts Comparison

In Figure 1.7, a series of line charts unfold a more granular examination of the aforementioned metrics. Here, each line delineates the performance trajectory of a specific model across the array of classes. This visualization lends insight into the variability inherent to each class while simultaneously revealing instances where the Optimized 3D CNN distinctly outshines its standard counterpart. The nuances captured in these lines underscore differential model efficacies, which might be attributed to the optimization processes.

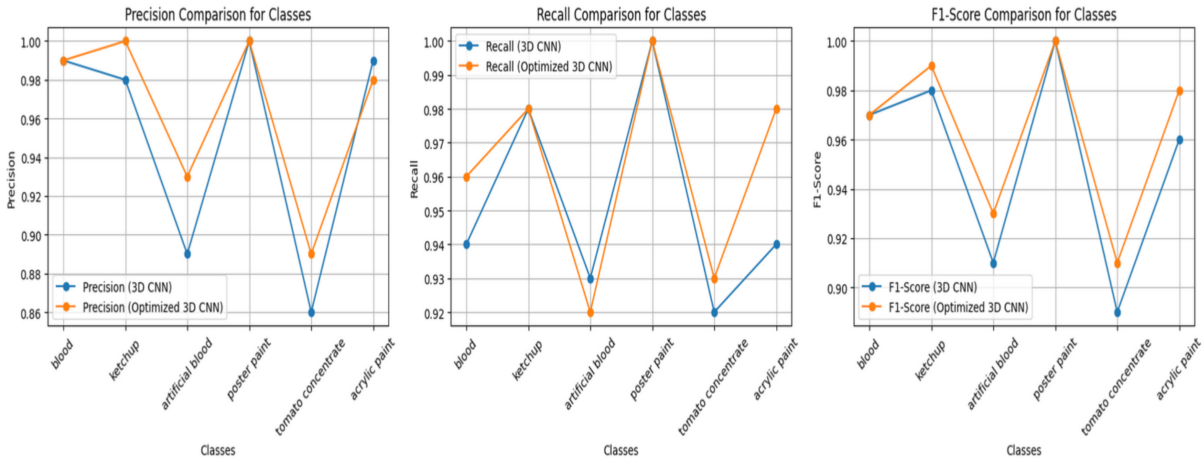


Figure 6.7: Recall Precision F1 Together Line Graph

Combined Line Chart

The convergence of precision, recall, and F1-score metrics into a single visual narrative is epitomized in Figure 1.8 . This comprehensive chart juxtaposes the performance data of both the standard and optimized models, applying a distinct color and line style for each metric and model type. This synergetic view facilitates a direct, simultaneous comparison of all three key metrics, thus illuminating the overarching performance trends and the intricate relationships among the metrics for each substance class. The visual synthesis presented here not only underscores the enhanced performance of the Optimized 3D CNN but also presents an intuitive mapping of metric interdependencies across classes.

In the synthesis of all visuals, we discern the performance gradient that favors the Optimized 3D CNN. While the qualitative assessment points to the superiority of the optimized model, the absence of numerical values or indications of statistical significance constrains us from a definitive quantitative affirmation of the enhancement level for each category.

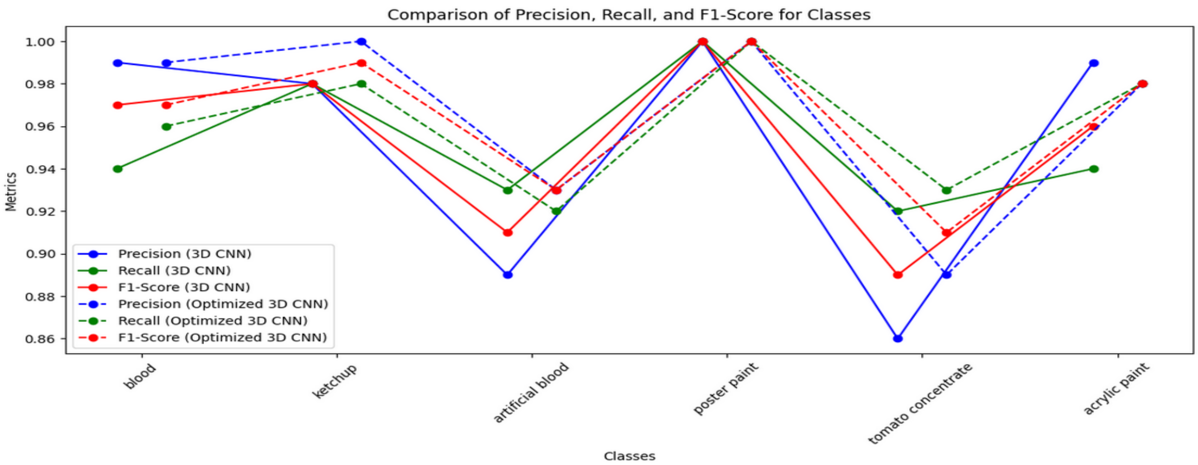


Figure 6.8: Combine Graph Recall,Precision and F1 score

6.3 Conclusion

This analysis refers application and enhancement of a 3D CNN model for classifying complex image data with high accuracy. By integrating advanced activation functions and optimizing the network architecture, the researchers have significantly improved the model's performance and efficiency. The detailed analysis of classification results underlines the potential of deep learning in practical applications, paving the way for further research and refinement in the field.

Chapter 7

Conclusion & Future Works

7.1 Introduction

In this chapter, a concise overview of the entire research is presented, covering the problem domain, previous studies, the novel contributions made, experimental analysis, and the conclusions drawn. Additionally, a brief glimpse into potential future directions for further research is provided.

7.2 Summary

In this experiment we apply a 3D CNN architecture [8] and optimize this architecture with some changes in model layers and use mish activation function instead of relu function. The optimized model gives better accuracy than the existing one. By applying the optimized 3D CNN model we get 97% accuracy which is higher than the existing 3D CNN (95%) and hybrid CNN(96%) model and parameters are reduced from 291895 to 125943.

The experiment detailed in this report represents a significant stride in the application of 3D Convolutional Neural Networks (CNNs) to complex classification tasks, emphasizing the adaptation and optimization of the model architecture to enhance performance significantly. This study introduced an optimized 3D CNN model, which incorporated several key innovations and strategic adjustments to the standard 3D CNN design, most notably in the activation functions used and the overall configuration of the network layers.

Central to the optimization process was the substitution of the traditional Rectified Linear Unit (ReLU) activation function with the Mish activation function. This change was predicated on the Mish function's non-monotonic nature and its inherent self-regularization properties, which are believed to contribute to mitigating the vanishing gradient problem—an issue that can impede the training of deep neural networks by reducing the gradient to an infinitesimally small value, thus stalling the learning process. The decision to use Mish was validated by the experiment's outcomes, where it demonstrated an enhanced capability to maintain active gradients through deeper layers of the network, thereby supporting more effective learning and generalization.

The architectural adjustments were not limited to the activation function alone. The overall structure of the CNN was refined to better suit the specific requirements and peculiarities of the dataset being used. This involved a comprehensive reevaluation of the network's layer configurations and parameter settings, which ultimately led to a significant reduction in the number of parameters—from 291,895 in the previous models to 125,943 in the optimized model. This reduction not only streamlined the model, making it faster and less resource-intensive but also helped in reducing overfitting, thereby enhancing the model's ability to generalize from the training data to unseen data.

The experimental setup was rigorously structured, with the dataset meticulously divided into three distinct sets: 5% for training, 5% for validation, and the substantial remainder, 90%, designated for the test set. This allocation was designed to rigorously evaluate the model's performance on a largely unseen test set, thus providing a robust measure of its real-world applicability and effectiveness. The results were compelling, with the optimized 3D CNN achieving an accuracy of 97%, surpassing the 95% accuracy of the existing 3D CNN and the 96% of the hybrid CNN model. This improvement underscored the benefits of the architectural optimizations and the use of the Mish activation function.

The evaluation of the model's performance was visually supported by Figure 8, which illustrated the overall accuracy comparison among the different models tested. This visual representation helped in clearly delineating the performance enhancements achieved through the optimization processes applied to the 3D CNN.

limitations of using Principal Component Analysis (PCA) for dimensionality reduction in this context. While PCA is a powerful unsupervised method for reducing dimensionality by transforming large sets of variables into a smaller one that still contains most of the information in large sets, it is limited to linear transformations of the data and does not leverage the class labels that could inform more discriminative reductions. Consequently, future work is slated to explore alternative non-linear dimensionality reduction techniques such as Linear Discriminant Analysis (LDA), Fisher Discriminant Analysis (FDA), and Partial Least Squares Regression (PLSR). These methods are not only capable of reducing dimensionality but also enhance the model's performance by utilizing class label information to achieve a more discriminative feature representation.

In summary, this experiment not only demonstrated the viability and effectiveness of optimized 3D CNN architectures in performing complex classification tasks but also set the stage for further exploratory studies into more sophisticated machine learning techniques that could offer even greater improvements in accuracy and efficiency. The switch to non-linear methods for dimensionality reduction represents a particularly promising avenue for future research, aiming at harnessing the full potential of the available data and driving the accuracy of classification models even higher.

7.3 Conclusion

For this experiment the whole dataset is divided into three separate sets. For training purpose 5% is used and 5for validation purpose and rest of the 90% is considered as test set .In this experiment mish function works well as it is a non monotonic function, possess self-regularization properties, vanishing gradient problem which makes it better than relu activation functions.

7.4 Future Work

The conclusions drawn from this study open several avenues for future research, which include:

- **Exploration of Non-Linear Dimensionality Reduction Techniques:** Given the limitations of PCA in leveraging class information and capturing non-linear relationships, future studies will investigate alternative methods. Techniques such as Linear Discriminant Analysis (LDA), Fisher Discriminant Analysis (FDA), and Partial Least Squares Regression (PLSR) will be explored for their potential to enhance model accuracy through more discriminative feature representation.

- **Integration of Class Label Information:** Future models will incorporate class label information in the dimensionality reduction process to improve the relevance and discriminatory power of the features extracted. This integration promises to refine the classification capabilities of neural networks in complex datasets.

- **Refinement of Activation Functions:** While the Mish activation function demonstrated significant benefits, there remains scope to explore and refine additional activation functions that might further mitigate issues like the vanishing gradient problem, or introduce benefits in specific types of neural network architectures.

- **Comparative Studies:** More comprehensive comparative studies involving existing models and the proposed improvements will be conducted to statistically validate the enhancements in various contexts and on diverse datasets.

- **Scalability and Efficiency Improvements:** The efficiency and scalability of the optimized 3D CNN model will be examined further to ensure its applicability in real-world scenarios that demand high computational efficiency, especially in systems with limited resources.

- **Application to Other Domains:** Extending the application of the optimized 3D CNN models to other domains such as video processing, medical imaging, or real-time surveillance to evaluate the adaptability and efficiency of the model across various fields.

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