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AI-Based Forensic Image Classification of Strangulation Marks

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Abstract

Strangulation is a critical forensic indicator often encountered in cases of homicidal violence. Accurately identifying strangulation marks is essential for reconstructing the events leading to death, determining the manner of death, and supporting legal proceedings. However, the process of identifying such marks is often subjective, relying heavily on the expertise of forensic pathologists. Variations in interpretation and human error can hinder the accuracy and consistency of forensic conclusions. In recent years, advancements in artificial intelligence (AI), particularly deep learning, have demonstrated promising capabilities in medical and forensic image analysis. This dissertation explores the application of a deep convolutional neural network—ResNet50—to classify strangulation marks from forensic images. The study aims to develop an automated, reliable, and efficient system that assists forensic experts in identifying strangulation patterns with greater objectivity. The methodology involves dataset collection, image preprocessing, model training, and performance evaluation using accuracy, precision, recall, and F1-score metrics. By leveraging the power of AI in forensic science, this study contributes to the growing body of research focused on integrating technology with forensic pathology, offering a potential tool for improving the speed and precision of forensic assessments in medico-legal contexts.

CHAPTER 1

INTRODUCTION

Forensic science plays a vital role in criminal investigations by applying scientific methods to examine evidence, piece together events, and determine the identity of those involved. Over time, progress in forensic science has greatly improved the accuracy of case resolutions. Despite these advancements, a major challenge persists in recognizing and classifying specific types of physical evidence, especially marks resulting from strangulation. Strangulation, a form of mechanical asphyxia, leaves marks on the body that may provide key insights into the circumstances surrounding a death. These marks, though indicative of a violent act, are often difficult to differentiate from other types of traumas. There is a clear need for dependable and effective techniques to accurately classify strangulation marks, particularly in suspected homicide cases where precise evidence is essential for legal outcomes.

Assessing individuals who have been subjected to strangulation is a routine responsibility for physicians specializing in clinical forensic medicine. The primary challenge in such cases is interpreting the findings in relation to the force and duration of the attack, as well as the potential threat it posed to the victim's life (T. Ha'rm et al., 1989). All types of strangulation—whether manual, throttling, or hanging—exert pressure on the airways, blood vessels, and neural structures in the neck (D.J. et al., 1989). Although these mechanisms of injury were documented as early as the late 19th century (Vischer, Ger. Med et al., 1896), the precise pathophysiological process that leads to death by strangulation remains partially unclear (A.M. Anscombe & B.H., 1996). Most forensic pathologists agree that vascular obstruction is the primary cause, while airway compression likely plays a lesser role (Arnold, 1996). Nevertheless, cerebral blood flow restriction alone does not fully explain the cause of death, as varying levels of brain damage from hypoxia may occur depending on the length of oxygen deprivation (Hawley et al., 2001).

Identifying strangulation marks requires a comprehensive understanding of their physical features as well as the situational context in which they appear, making the process highly complex. Although skilled professionals are capable of making accurate evaluations, the possibility of human error remains, and differences in individual interpretations often result in inconsistent classifications. This subjectivity poses a major obstacle in forensic investigations, as misidentification or inconsistent analysis of strangulation marks can significantly influence the outcome of legal cases. Additionally, depending on personal judgment in forensic assessments can slow down the investigative process and complicate the presentation of clear, objective evidence in court. Strangulation is recognized as one of the strongest indicators of potential homicide and is identified in approximately 10% of deaths caused by trauma (Strack & Gwinn, 2011).

It is estimated that only 11Ib of pressure applied to both carotid arteries for 10 s leads to unconscious. Brain death can result if this pressure is sustainable for 4-5 min [McCance & Huether, 2010; Strack & McClane, 1999]. More than half of U.S. states have enacted laws specifically addressing strangulation; however, it is often underreported or downplayed by victims (Turkel, 2010). Although strangulation can occur with a small amount of pressure to the neck, it can be easily missed by a health care provider because there may be no physical findings. The absence of visible injuries or the presence of delayed and nonspecific symptoms often leads to underreporting of strangulation incidents, making clinical evaluation complex and difficult (Clarot, Vaz, Papin & Strack, 2009). Despite this lack of external evidence, victims may suffer from severe internal injuries, including respiratory or neurological complications, that necessitate medical attention. In some cases, individuals subjected to strangulation may succumb to their injury's days or even weeks after the incident (Gwinn, McClane, Shanel-Hogan & Strack, 2004).

TYPES OF STRANGULATION

Manual: Manualise the most common type of strangulation and is used when the assailant's hands are used to compress the victim's neck. Manual strangulation occurs in 83% of strangulation cases (Shields et al., 2010).

Choke Hold: This method involves the attacker wrapping their arm around the victim's neck from behind, with the elbow bent, applying pressure simultaneously to both sides of the neck. Often, this technique leaves no visible external injuries (Dix & Cala Luce, 1998).

Ligature Strangulation: In this form, a cord-like object—such as a rope, belt, or scarf—is used to tighten around the neck, causing compression and potentially fatal results.

Postural Strangulation: This occurs when the victim is unable to breathe due to the positioning of their body—for instance, if the assailant sits on the victim's chest, restricting respiratory movement and leading to suffocation.

Hanging: A hanging involves the use of a noose around the victim's neck and the weight of the victim's body to cause compression on the neck.

Mechanism of injury Compression of the neck or applying pressure to the neck can cause significant injury in the following ways:

Venous Congestion: The jugular veins are the vessels in the neck that carry deoxygenated blood from the brain back to the heart. Only a minimal amount of pressure, 4.5 lb, is needed to close the jugular veins. Closure of the jugular veins causes stasis of the blood within the vessels of the brain, leading to unconsciousness and cerebral hypoxemia (McCance & Huether, 2010).

Arterial Obstruction The carotid arteries are the vessels in the neck that carry oxygenated blood to the brain. A little more pressure, 11 lb for 10 s, is needed to occlude the carotid arteries. If this pressure is immediately released, blood flow should be restored and consciousness may be regained, but if this pressure continues for 4–5 min, death will result. Closure of the carotid arteries stops this vital blood supply to the brain, leading to unconscious ness and cerebral hypoxemia (McCance & Heuther, 2010). Petechial haemorrhages will not necessarily occur because blood can escape through the jugular veins (e.g., lack of negative intracranial pressure).

Airway Obstruction This is uncommon as 33 lb of pressure is needed to close the trachea. Closure of the trachea prevents oxygen from entering the lung, causing asphyxia (McCance & Heuther, 2010).

Carotid Sinus Pressure With strangulation, there is the possibility of pressure being placed on the carotid sinus, which can cause cardiac dysrhythmias and arrest. However, this outcome is uncommon as it requires pressure to be exerted on a specific region continuously for around 3–4 minutes (Clarot et al., 2005). Regardless of the mechanism, a strangulation victim will suffer intense pain before losing consciousness, eventually followed by death (McClane, Strack,&Hawley,2001).

In recent years, many strangulation cases have been increasingly treated as felonies due to a growing awareness among professionals of the dangers associated with strangulation. Law enforcement officers and prosecutors are either applying current laws or collaborating with lawmakers to draft new felony legislation. Specialized documentation tools have been created to assist legal and medical personnel in identifying and recording strangulation-related injuries. Medical professionals, forensic nurses, and investigators are being called upon as expert witnesses in court proceedings. Training programs on strangulation are also being conducted at multiple conferences and some police academies, often using instructional videos developed in San Diego [Strack & Gwinn, 2011].

There is a rising need for a more systematic, technology-driven, and precise method for classifying strangulation marks. Recent progress in artificial intelligence (AI), especially deep learning methods, provides a promising approach. AI has proven effective in several domains, including medical diagnostics and self-driving technology, by analyzing vast datasets and uncovering patterns with high precision. In forensic science, AI is being adopted in various tasks such as image analysis, where it can help categorize forensic evidence, including wounds, injuries, and subtle marks that could be missed by human examiners. Forensic Sciences include technical processes conducted to detect crimes and identify criminals through examining and assessing physical evidence obtained from legal and administrative investigations. This field also seeks to establish relationships among the crime, crime scene, victim, and offender, applying a range of scientific techniques to aid justice (Suzanne, 2019). One of the most essential components in any forensic examination is the crime scene and associated findings. When properly analysed during forensic investigations, it follows a structured and evidence-based method. Technological progress, particularly in modern and versatile approaches, has led to more thorough and diverse evaluations of materials collected at crime scenes. Among the leading innovations is artificial intelligence (AI). AI is a computer science discipline aimed at resolving cognitive challenges tied to human intelligence by simulating specific abilities in a digital context and subsequently executing related functions (Luger, 2009). Artificial intelligence utilizes trained systems that emulate human cognitive processes (Russell & Norvig

P 2021), particularly in analyzing intricate information (Hosny et al., 2018). Unlike conventional systems, AI models are not bound by rigid instructions and can tackle problems independently (Mergagliotti G & Bolle T 2019). Deep learning is a branch of artificial intelligence that relies on neural networks to work with a wide array of tasks like analyzing images, texts, and speech (Lecun et al 2015, Krater et al., 2020). While AI and deep learning applications have significantly transformed the healthcare sector and several medical areas (Yu K & Beam A 2018, Rajkumar et al., 2019), their implementation in forensic science has been minimal (Nikita & Nikitas 2020) and often limited to fields outside forensic pathology. This is somewhat unexpected, considering the visually driven nature of forensic pathology across both micro and macro levels.

The development of this concept brought forth the idea of "Machine Learning" (ML), where a machine learns from experience without a complex coding structure. This method is based on teaching the model using datasets. The term "Deep Learning" (DL) was introduced in 1986 by Rina Dechter as a subfield of ML. DL is seen as a technique for performing ML by mimicking the structure of neural networks found in the human brain. Later, in 2000, the term "artificial neural network" (ANN) was officially introduced by Igor Aizenberg and colleagues (Aizenberq et al., 2000).

The core of this dissertation revolves around examining the use of deep learning—particularly the ResNet50 framework—in the classification of strangulation marks. ResNet50, a type of convolutional neural network (CNN), is recognized for effectively managing complex image inputs and precisely detecting features in visual data. This research intends to apply ResNet50 to automate the identification of strangulation marks in forensic imagery, aiming to assist forensic specialists with a dependable, unbiased system that minimizes human mistakes and accelerates the forensic evaluation process. The project includes training a deep learning model on a dataset comprising annotated forensic images of strangulation marks, enabling the model to understand and detect distinct traits related to strangulation. The central aim of this research is to determine whether the ResNet50 deep learning network can efficiently identify strangulation marks from forensic images. The model's outcomes will be analysed by comparing its predictions to assessments made by forensic experts and by evaluating its ability to perform across multiple datasets. Automating this segment of forensic evaluation is expected to improve the accuracy of detecting strangulation marks, lessen the time needed for forensic processing, and offer a more standardized tool for forensic professionals.

The importance of this study stems from its potential to transform forensic science by introducing AI-driven systems that can streamline the investigative workflow and elevate the precision of forensic assessments. By implementing deep learning networks like ResNet50, the study proposes an innovative solution to an ongoing issue in forensic investigations. In addition, the findings may promote broader AI usage within forensic contexts, enhancing the interpretation of other injuries and forensic materials. Integrating AI into forensic assessments may lead to more reliable and standardized procedures in criminal casework, thereby supporting the justice framework.

To create an artificial intelligence-powered model for classifying forensic images of strangulation marks, thereby improving the accuracy and effectiveness of medico-legal evaluations. The study's objectives are as follows:

1. To gather and preprocess forensic image datasets featuring strangulation marks for AI model training.
2. To develop and train a convolutional neural network (CNN), specifically ResNet50, to classify various types of strangulation marks.

3. To measure the model's performance through standard evaluation metrics like accuracy, precision, recall, and f1-score.
4. To analyse the model's effectiveness and feasibility in real-world forensic investigations for supporting forensic professionals.

CHAPTER 2

REVIEW OF LITERATURE

2.1 Forensic Science and Strangulation Mark Identification

Strangulation is a significant contributor to mechanical asphyxia and is commonly associated with homicidal incidents. Detecting strangulation marks involves the observation of different types of external neck trauma, including petechiae, bruises, abrasions, and ligature impressions. Because distinguishing between ante-mortem and post-mortem trauma can be complex, forensic experts often employ histological approaches such as immunohistochemistry to determine injury vitality (Madea, 2017; Maiese et al., 2021).

2.2 Background of Forensic Science and Strangulation Mark Identification

Forensic science plays a pivotal role in the criminal justice system by providing crucial insights into the events surrounding a crime. It involves the use of scientific principles and methodologies to analyse physical evidence collected from crime scenes. Among the various disciplines within forensic science, forensic pathology is particularly focused on determining causes of death and injury through the examination of bodies and bodily fluids. One of the most challenging forms of evidence encountered in forensic pathology is the identification of strangulation marks.

Strangulation is a form of mechanical asphyxia where pressure is applied to the neck, causing obstruction to airflow and circulation. It often leads to visible marks such as bruising, contusions, and other skin impressions that can provide vital clues about the method of death. However, the differentiation of strangulation marks from other types of injury, such as those caused by blunt force trauma, is not always straightforward. This is because the physical appearance of strangulation marks can vary greatly depending on factors such as the individual's skin type, the duration of the constriction, and the amount of force applied. As a result, the accurate identification and classification of strangulation marks rely heavily on the subjective judgment of forensic pathologists (Smith et al., 2020).

2.3 Challenges in Current Strangulation Mark Identification Methods

Current methods for classifying strangulation marks often involve a combination of visual inspection, manual measurements, and expert interpretation. While experienced forensic pathologists can often provide a fairly accurate diagnosis, the process remains prone to error due to inter-observer variability. Different experts might offer varying opinions on the nature of the marks based on their personal experience and training. This subjectivity is particularly problematic in the context of criminal investigations, where the misinterpretation of evidence can lead to wrongful convictions or the failure to identify perpetrators (Jones & Taylor, 2018).

Moreover, forensic pathology often involves the analysis of images taken from crime scenes or autopsies, which can be of varying quality and resolution. As a result, marks that are subtle or difficult to identify may go unnoticed or misclassified. These issues underline the need for more objective and reproducible methods for analysing strangulation marks, which is where the application of artificial intelligence (AI) comes into play.

2.4 The Role of Artificial Intelligence in Forensic Science

In recent years, artificial intelligence has emerged as a promising tool for improving accuracy and efficiency across various fields, including medicine, engineering, and law enforcement. Specifically, deep learning algorithms—particularly convolutional neural networks (CNNs)—have shown exceptional potential in image classification tasks, including those within the realm of medical and forensic imaging (Zhang et al., 2019). By automating the process of image analysis, AI models can reduce the human error factor and ensure that all marks are identified and classified consistently.

In forensic science, AI offers the potential to assist pathologists by classifying strangulation marks with a level of accuracy that surpasses traditional methods. The key advantage of using AI is that it can be trained to recognize patterns in images that might be overlooked by the human eye. By training AI models on large datasets of annotated forensic images, researchers can develop systems capable of providing more reliable results while reducing subjectivity in the analysis process (Liu et al., 2021

2.5 The ResNet50 Architecture and Its Application

One of the most powerful deep learning models for image classification tasks is the ResNet50 architecture, a type of convolutional neural network. ResNet50 is known for its ability to handle very deep neural networks through the use of residual learning, which allows the network to learn more efficiently and prevent the degradation problem that typically arises in deeper networks (He et al., 2015). This characteristic makes ResNet50 particularly suitable for complex tasks, such as classifying forensic images of strangulation marks.

The architecture consists of 50 layers, making it deeper and more accurate than simpler models. The model's ability to learn from vast amounts of data allows it to identify features in images with high precision. ResNet50 has already demonstrated impressive results in various applications, such as medical image analysis, where it has been used to identify different types of tumours and other abnormalities (Ronneberger et al., 2015). Given these capabilities, the application of ResNet50 to the classification of strangulation marks holds great promise.

2.6 Integration of AI in Strangulation Mark Classification

Though the direct application of AI in the classification of strangulation marks is sparse, the potential is evident. AI models have been successfully implemented for the detection of other types of wounds, such as bruises and contusions (Tolosana et al., 2022). The integration of AI could enhance the analysis of strangulation marks by providing an objective, reproducible method for identifying subtle patterns that may be overlooked by human experts.

2.7 General Overview of Artificial Intelligence

AI has a deep-rooted history and has undergone a remarkable evolution over time. This evolutionary process has led to subfields the emergence of various within AI, forming the foundational concepts of the field. The algorithms used in AI consist of procedures that enable computer-based machines to perform human-like tasks, learn from experiences, and adapt to new inputs, helping computers solve problems on various scales (Bengio & LeCun, 2007). Each subfield and its algorithms contribute to the overall functioning of AI by offering unique techniques and methods. Among these subfields, learning, machine learning, deep and natural language processing stand out as key areas.

2.8 Machine learning (ML)

ML (Machine Learning) is a comprehensive field focused on creating predictive models or identifying groups within data. At its core, ML aims to objectively replicate the human ability to recognize specific patterns through computational calculations. This field becomes particularly relevant when the dataset being analysed is either very large or very complex automating the data analysis process and making it repeatable (Greener et al., 2021). ML algorithms play a crucial role in all these processes and are divided into three main categories: supervised, unsupervised, and reinforcement learning (Bishop, 2006; Sarker, 2021). Supervised learning is based on an existing input-output set and is used to generate appropriate outputs for previously unseen data. In unsupervised learning, only input data is available, and algorithms are trained to understand patterns within this data, which can also be used for clustering and detecting anomalies in datasets. Reinforcement learning enables software to learn through interactions with its environment and is based on the trial-and-error principle, where responses to encountered situations lead to rewards or penalties (Han et al., 2022; Mohammed et al., 2016; Stone, 2023).

2.9 AI Applications in Digital Forensics

Digital forensics is defined as the process information of obtaining valuable and evidence from computing devices within a legal framework, and it is widely used by law enforcement and various organizations (Al Fahdi et al., 2016; Casey, 2010). AI plays a significant role in digital forensics due to its ability to rapidly process large datasets, perform complex analyses, and utilize DL algorithms for detecting digital traces (Al Fahdi et al., 2016). Digital forensics faces challenges such as growing data storage capacities, the widespread use of flash drives, and the need to analyse numerous devices (Casey & Stellatos, 2008; Garfinkel, 2010). While many forensic tools offer "Push-Button Forensics" functionality that automates basic procedures, manual and cognitive evolution is still necessary for the data analysis This places a burden on investigators, causing law enforcement to shift from a gold-standard approach to an intelligence-based one (Al Fahdi et al., 2016; Lawton et al., 2014).

2.10 Risks, Ethical, and Legal Dimensions of AI Use in Forensic science

forensic science applies a range of scientific techniques and methods to clarify criminal cases, apprehend perpetrators, and protect the rights of the innocent (Suzanne, 2019). AI technologies, which reduce, improve, or accelerate these processes, have become critical in forensic science. The use of AI in various fields of forensics, such as forensic genetics, forensic medicine, and crime scene investigation, enables the rapid and efficient processing of large datasets, extraction of meaningful information, cost reduction, increased efficiency, and minimization of human error (Ahmed Alaa El-Din, 2022; Gupta et al., 2020; Singh Sankhla et al., 2020). However, integrating AI into forensic science has introduced several ethical and legal concerns.

2.11 Strangulation Forensic Examination

In recent years, many strangulation cases are being elevated to felony-level prosecution due to increased awareness among professionals regarding the lethality of such acts. Law enforcement agencies and prosecutors are either using existing legal provisions or collaborating with legislators to establish new felony laws. Specialized documentation tools have been developed to aid legal and medical professionals in recording patient injuries and identifying symptoms of strangulation. Medical practitioners, forensic nurses, and detectives are increasingly serving as expert witnesses in court. Moreover, training on strangulation recognition is being incorporated into conferences and regional police academies, often supported by instructional videos developed in San Diego (Strack & Gwinn, 2011).

2.12 An Improved ResNet50 for Environment Image Classification

In deep learning, channel fusion techniques are crucial for enhancing model performance, primarily through concatenation, summation, and multiplication. Concatenation allows the combination of feature maps at different levels in the depth dimension, enhancing the model’s feature representation capability, commonly seen in encoder decoder structures where low-level and high-level features are combined. Summation fusion, by adding multiple feature maps element-wise, helps balance feature contributions and reduce noise interference. Multiplication fusion emphasizes the importance of features by element-wise multiplication, enhancing the model's ability to capture details and semantic information. These methods process information in different ways, each having its advantages and applications in practice. Unlike previous work, we reconsidered the dimensions of model input. To better focus the model on the target area without significantly increasing model complexity, we adopted a feature fusion approach using concatenation. This method retains original background information while allowing subsequent processes to direct the model's attention to the target area (Bingchan Li et al., 2014) This paper enhances the traditional ResNet50 residual network by incorporating differential convolutions and attention mechanisms, significantly improving the detection accuracy of blue-green algae in water bodies. Future research will focus on simplifying network parameters and speeding up computations to enable deployment on industrial devices with limited resources, thereby improving system compatibility and classification efficiency. We also plan to explore Vision Transformer (ViT) models, which may offer better parallelism and performance. This will involve a comparative study to evaluate the benefits and trade-offs of using ViT. Additionally, we will investigate advanced attention mechanisms beyond the Convolutional Block Attention Module (CBAM) to further enhance feature representation (Bingchan Li et al., 2014).

2.13 A Systematic Review of Past and Current Applications and Future Perspectives Forensic Pathology (FP)

The AI revolution has significantly impacted various areas of medicine, including forensic pathology. Multiple branches such as forensic anthropology, forensic odontology, estimation of postmortem interval (PMI), and cause of death (COD) analysis can benefit from AI and machine learning algorithms. Despite the promising potential, many of the technologies assessed in this systematic review exhibit limitations. Larger datasets and improved computational hardware may help overcome these challenges. This review emphasizes the importance of AI in forensic pathology, comparing different technologies and providing technical insights. It advocates for the development of new AI algorithms to support—but not replace—forensic experts in their daily work (Ioannis et al., 2024).

2.14 Application of Deep Learning in Forensic Pressure Mark Classification

Deep learning has increasingly been applied to forensic image analysis, with convolutional neural networks (CNNs) demonstrating notable success in classifying injury patterns such as bruises and pressure marks due to their powerful spatial feature extraction capabilities. While CNNs like AlexNet, VGG16, and ResNet50 have shown promise in detecting and differentiating injuries, they often fall short in capturing the temporal progression of such marks. To address this limitation, recent studies have explored hybrid architectures that integrate CNNs with Long Short-Term Memory (LSTM) networks, allowing for the modelling of both spatial and temporal characteristics in injury images. However, there remains a significant gap in forensic research leveraging this hybrid approach, particularly in the automatic classification of pressure marks—a challenge the current study seeks to overcome by proposing a novel CNN-LSTM model tailored for this task (Kumar et al., 2024).

2.15 Advancement in Forensic Imaging

Forensic image analysis has become a vital tool in documenting and examining physical injuries. High-resolution imaging techniques, such as dermatoscopy and multispectral photography, enable clearer visualization of trauma patterns. According to Chandra and Dixit (2020), digital imaging in forensic medicine enhances the precision of evidence documentation, especially in soft tissue analysis.

2.16 AI and Deep Learning in Medical and Forensic Image Analysis

Artificial Intelligence (AI), particularly deep learning, has shown immense promise in the field of image classification. Convolutional Neural Networks (CNNs), including architectures like ResNet50, have been successfully employed in various domains such as skin lesion detection, fracture diagnosis, and hemorrhage identification. For instance, Esteva et al. (2017) demonstrated that CNNs can classify skin cancer at dermatologist-level accuracy using thermoscopic images.

2.17 Application of AI in Injury Classification

Emerging studies have explored using deep learning for detecting injury patterns, such as bruises, burns, or fractures. These systems automate feature extraction and classification with high accuracy. For example, a study by Sagar et al. (2021) used deep learning to classify injury types in forensic photographs, highlighting improved consistency over human examiners.

2.18 Challenges in AI-based Forensic Analysis

Despite the potential, the implementation of AI in forensic science faces challenges such as dataset scarcity, image quality variation, and ethical concerns. Models must be trained on diverse, annotated forensic images to improve generalization. Another concern is the legal admissibility of AI-generated evidence, which still requires human expert corroboration.

2.19 Recent Developments in Strangulation Mark Classification

Recent works have focused on creating datasets specifically of strangulation marks and training models like ResNet50 to distinguish them from other trauma. The uploaded research indicates preliminary attempts to classify such marks using pretrained networks with fine-tuning and augmentation strategies to address overfitting due to limited data.

2.20 AI in Forensic Classification of Strangulation Marks

Strangulation-related deaths pose a significant forensic challenge due to the subtle and varied nature of neck injuries. Traditional analysis relies heavily on expert interpretation of external marks, which can be subjective. Recent developments in artificial intelligence (AI), particularly convolutional neural networks (CNNs), offer a more objective and automated approach to classifying strangulation marks. Studies have shown that deep learning models like ResNet50 can extract meaningful patterns from forensic images, improving accuracy in distinguishing between ligature and manual strangulation marks (Sharma et al., 2024). However, challenges remain regarding standardized datasets and the need for interpretability in forensic applications. Despite these limitations, AI shows strong potential to enhance consistency and reliability in forensic image analysis.

2.21 Forensic Identification of Strangulation Marks

Strangulation remains a critical concern in forensic pathology, often presenting with subtle or ambiguous signs. Differentiating between manual, ligature, and hanging marks is essential yet challenging due to overlapping external injuries such as abrasions, contusions, and petechiae. Traditional analysis relies on expert interpretation, but advances in artificial intelligence (AI) offer new tools for classifying these marks based on image features. Deep learning models like ResNet50 can assist in identifying injury patterns with greater consistency and objectivity. Despite promising outcomes, the lack of standardized forensic datasets and the need for explainable AI remain ongoing concerns (Hunsaker et al., 2020; Sharma et al., 2024).

2.22 Based Radiomic Model for predicting strangulation risk

Wang et al. (2022) developed a radiomic model using CT images to predict the risk of bowel strangulation in patients with acute small bowel obstruction. By extracting 107 radiomic features and applying logistic regression, they built a model that showed strong diagnostic performance. The model outperformed both radiologists and conventional CT signs, achieving an AUC of 0.91 in the validation set. This tool could assist clinicians in early identification of high-risk cases and improve surgical decision-making.

2.23 Deep Learning for Forensic Image Analysis

Deep learning, particularly Convolutional Neural Networks (CNNs), has demonstrated remarkable success in the classification of medical and forensic images. CNNs excel at extracting hierarchical features from images, making them an ideal choice for tasks like image classification. One of the most prominent architectures for CNN-based image classification is ResNet50 (Residual Networks), which has shown substantial improvements over traditional CNNs. Introduced by He et al. (2015), ResNet50 uses residual connections, which allow it to train deeper networks without the vanishing gradient problem, enabling the extraction of complex features from images.

In forensic injury detection, pre-trained CNNs, like ResNet50, are commonly used to extract general visual features from images before fine-tuning them for domain-specific tasks. This transfer learning approach has been highly effective in forensic domains, as it allows the use of pre-trained models on large datasets like ImageNet, which provides general feature extraction capabilities. Once the model is fine-tuned with specific forensic data, it can learn to distinguish between injury types with high accuracy (LeCun et al., 2015). Previous research in forensic injury classification, such as the work by Röhrich et al. (2021), has demonstrated the effectiveness of using pre-trained CNNs, such as ResNet50, for distinguishing between different types of injuries.

2.24 Data Preprocessing and Augmentation in Forensic Image Classification

Preprocessing and data augmentation are critical components of any image classification pipeline. Preprocessing ensures that the input data is in the correct format for model input, while augmentation helps in increasing the diversity of the dataset, which is crucial for preventing overfitting. A common preprocessing step is resizing images to a uniform size, which is done to ensure that all images have consistent input dimensions, a necessary condition for deep learning models like ResNet50 (He et al., 2015). The practice of normalizing image pixel values is also standard, as it ensures that the values are within a smaller range, helping to stabilize the training process (Ioffe & Szegedy, 2015).

Data augmentation techniques, such as random rotations, zooms, and horizontal flips, are often applied in image classification tasks to artificially expand the dataset. These transformations simulate realistic variations in images without altering the underlying semantic content, making the model more robust. Research has shown that data augmentation plays a vital role in enhancing the performance of image classifiers, particularly when dealing with limited datasets (Shorten & Khoshgoftaar, 2019).

2.25 Evaluation Metrics for Classification Models

The evaluation of image classification models involves the use of several metrics to gauge the model's performance. Precision, recall, and F1-score are commonly used to evaluate the classification performance, as they provide a balanced view of the model's ability to correctly classify positive and negative cases. Precision reflects the proportion of true positive predictions relative to all positive predictions, while recall focuses on the model’s ability to identify all actual positive cases. The F1-score, the harmonic mean of precision and recall, is especially valuable when dealing with imbalanced datasets (Pedregosa et al., 2011).

Another important evaluation tool is the confusion matrix, which shows the distribution of true positives, true negatives, false positives, and false negatives. This matrix is especially useful in binary classification tasks, such as distinguishing between strangulation and non-strangulation marks, as it provides insight into where the model is making errors (Fawcett, 2006). In the context of forensic injury classification, a confusion matrix can help pinpoint misclassifications, allowing for targeted improvements in the model.

2.26 Transfer Learning and Model Fine-Tuning

Transfer learning, as applied in this methodology, involves using a pre-trained model and adapting it to a specific task through fine-tuning. This method is highly beneficial when working with smaller datasets, as it leverages knowledge from large-scale datasets (like ImageNet) and adapts it to a new task. In the case of forensic image classification, transfer learning helps the model learn useful features such as edges, textures, and shapes from a large, diverse dataset, which are then refined to classify forensic images of strangulation marks (Yosinski et al., 2014). The use of a pretrained ResNet50 model allows the study to focus on optimizing the task-specific layers while leveraging the powerful feature extraction capabilities of the pre-trained network.

CHAPTER 3

MATERIALS AND METHODS

3.1 Methodology

This study implemented an AI-based image classification pipeline to distinguish strangulation marks from non-strangulation injuries in forensic images. Following established practices in image classification, the dataset was organized into separate class-based directories for training and validation. An AI model capable of classifying strangulation marks using a transfer learning approach with the ResNet50 architecture. The methodology consists of the following key steps. Figure 1 shows the workflow of proposed work (Oswal, Shrenik, et al.) and (Lehner, R., et al.)

3.2 Workflow of proposed work

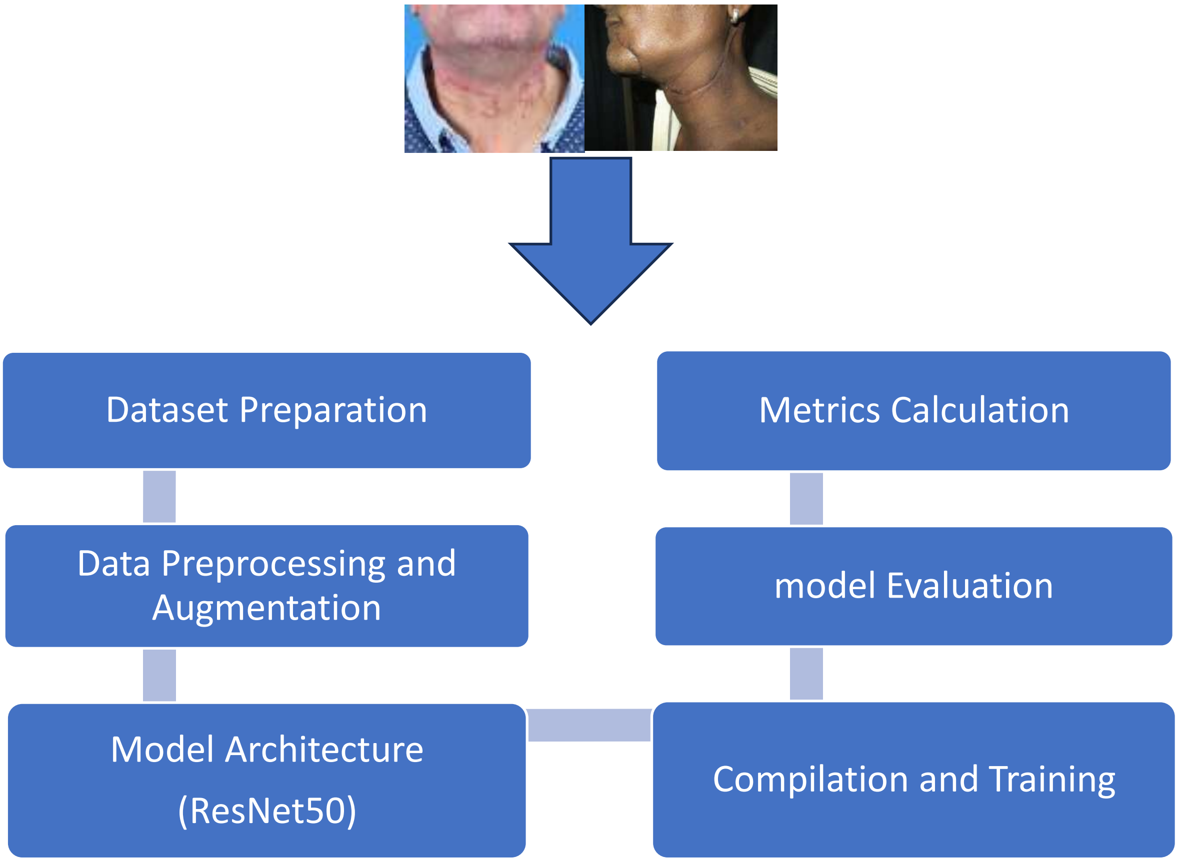
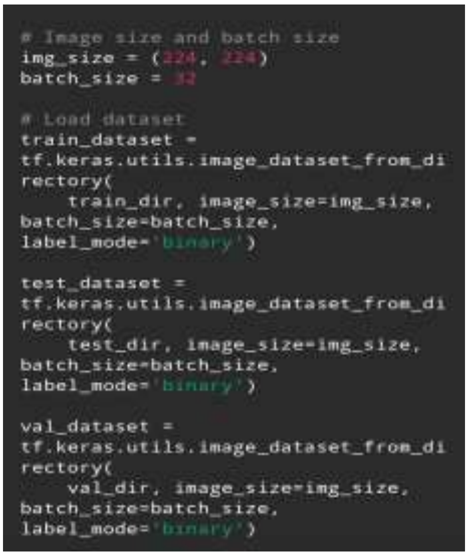


Figure 1: Workflow of proposed work

3.3 Proposed solution

3.3.1 Dataset Preparation

The dataset used in this study comprises labelled image of two classes: strangulation and non-strangulation. These images were sourced from verified forensic image database, publication, and open-access academic datasets, ensuring ethical usage. The dataset consisted of two balanced classes: image depiction strangulation and non-strangulation mark cases. For each class, 250 image where used, out of which 200 image (80%) were allocated for training and 50 image (20%) for training and 50 image (20%) for validation. This 80:20 split ensures sufficient data for learning while maintaining an independent set for evaluate model performance. Each image was carefully resized to a uniform dimension of 224x224 pixels to match the input requirements of ResNet50 as shown in figure 2 shows the python code for loading and splitting the dataset into Training, Validation, and testing sets using TensorFlow Figure 3 shows the sample images used for binary classification-(left) strangulation mark (right) non-strangulation mark.



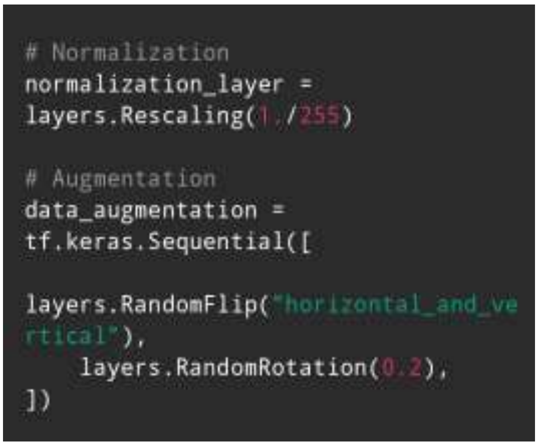
```
# Image size and batch size
img_size = (224, 224)
batch_size = 32

# Load dataset
train_dataset =
tf.keras.utils.image_dataset_from_di
rectory(
    train_dir, image_size=img_size,
batch_size=batch_size,
label_mode='binary')

test_dataset =
tf.keras.utils.image_dataset_from_di
rectory(
    test_dir, image_size=img_size,
batch_size=batch_size,
label_mode='binary')

val_dataset =
tf.keras.utils.image_dataset_from_di
rectory(
    val_dir, image_size=img_size,
batch_size=batch_size,
label_mode='binary')
```

Figure.2 Code snippet for loading and preparing the image dataset using TensorFlow's image dataset from directory method

Figure.3 (a)Strangulation (Oswal, Shrenik, et al) (b)Non-Strangulation (Lehner, R., et al.)

3.3.2 Data Preprocessing and Augmentation

To enhance the model's ability to generalize and minimize overfitting, preprocessing methods like normalization and data augmentation were utilized. Normalization adjusts pixel values to a range between 0 and 1. Data augmentation involves random flips and rotations to mimic variations in the images. Figure 4 illustrates the code snippet for preprocessing, augmenting, and loading the image data into the training, validation, and testing sets using TensorFlow.



```
# Normalization
normalization_layer =
layers.Rescaling(1./255)

# Augmentation
data_augmentation =
tf.keras.Sequential([

layers.RandomFlip("horizontal_and_ve
rtical"),
    layers.RandomRotation(0.2),
])
```

Figure.4 Data preprocessing and augmentation

3.3.3 Model Architecture

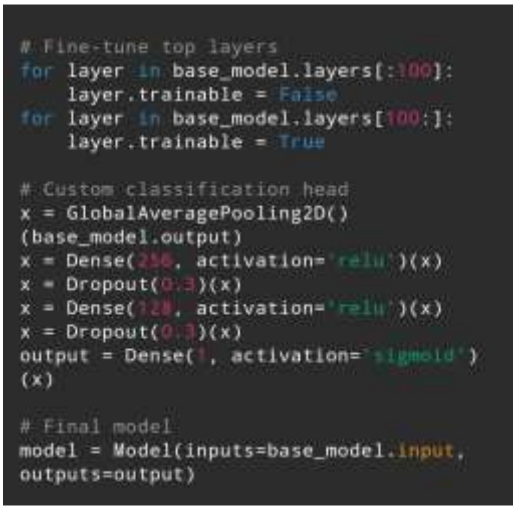
The classification model was constructed using the ResNet50 convolutional neural network architecture. Originally introduced by He et al. (2015), ResNet50 employed residual learning to efficiently train very deep networks. In this study, the ResNet50 model was loaded with pretrained weights from ImageNet (weights='ImageNet') and its original fully connected top layers were excluded (include top=False). This configuration allowed ResNet50 to act as a fixed feature extractor: all layers in the ResNet50 base were frozen (trainable=False), preventing any updates to the pretrained filters during training. This transfer learning approach was effective because the convolutional base captured general visual features such as edges, textures, and shapes that were valuable across diverse image domains.

On top of the frozen ResNet50 base, custom classification layers were added. First, a Global Average Pooling 2D layer condensed the spatial feature maps into a single feature vector per filter. This global pooling method replaced traditional flattening, helping to reduce overfitting by summarizing each feature map. The output vector was then passed through one or more fully connected (Dense) layers—for example, a Dense layer with 256 units and ReLU activation, followed by a Dropout layer (with a dropout rate of 0.3) for regularization. Additional Dense and Dropout layers, such as 128 units followed by 64 units, were included as needed. Finally, the output layer consisted of a Dense layer with a sigmoid activation function; since this was a binary classification task (strangulation vs. non-strangulation), the output had one neuron that produced probabilities for the two classes.

In summary, the model architecture, illustrated in Figure 5, used ResNet50 for feature extraction combined with a custom classification head. It incorporated data augmentation, normalization, and a sigmoid output layer for binary classification.

Model Architecture:

- Input layer: Accepted resized RGB images of size 224 x 224 x 3
- ResNet50 base (initially frozen): Pretrained on ImageNet, excluding the top classification layers
- Global Average Pooling layer: Converted feature maps into a single 1D vector per image
- Dense layer (256 units) with ReLU activation: Learned complex features from the pooled vector
- Dropout layer (rate 0.3): Helped prevent overfitting
- Output layer (1 unit): sigmoid activation for binary classification



```
# Fine-tune top layers
for layer in base_model.layers[:100]:
    layer.trainable = False
for layer in base_model.layers[100:]:
    layer.trainable = True

# Custom classification head
x = GlobalAveragePooling2D()
(base_model.output)
x = Dense(256, activation='relu')(x)
x = Dropout(0.3)(x)
x = Dense(128, activation='relu')(x)
x = Dropout(0.3)(x)
output = Dense(1, activation='sigmoid')
(x)

# Final model
model = Model(inputs=base_model.input,
outputs=output)
```

Figure.5 Architecture based on ResNet50

3.3.4 Compilation and Training

After defining the model architecture, the next crucial step was to compile and train the model to optimize its weights based on the training data. Compilation specified how the model was configured for learning, including the optimization algorithm, loss function, and performance metrics.

Compilation strategy

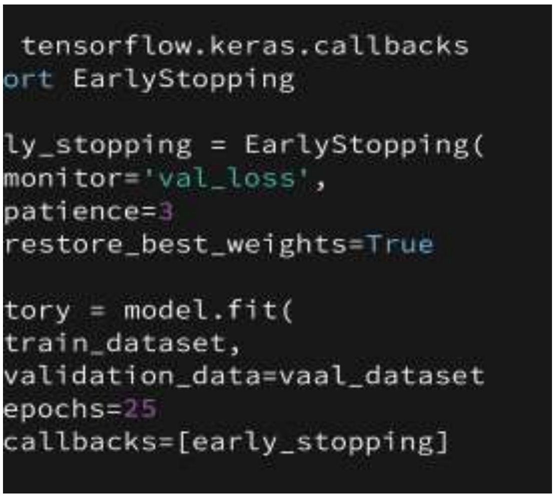
The model was compiled using the Adam optimizer, which was well-suited for problems involving sparse gradients and noisy data. The binary cross-entropy loss function was employed as the classification task involved two distinct classes: strangulation and non-strangulation. To monitor the model's learning progression, accuracy was chosen as the evaluation metric. Figure 6 displayed the code used to compile the model with the Adam optimizer, binary cross-entropy loss, and accuracy as the evaluation metric.

```
model.compile(
    optimizer='adam',
    loss='binary_crossentropy',
    metrics=['accuracy']
)
```

Figure.6 Model Compilation setting: Optimizer Loss Function, and Performance Metric

Training Process

The model was trained using the pre-processed and augmented training dataset, while the validation dataset was used to monitor performance and detect overfitting. Training was conducted over 25 epochs, with an Early Stopping callback employed to avoid overtraining beyond the point of optimal model performance. This callback monitored the validation loss and terminated training if no improvement was observed for a specified number of consecutive epochs (patience threshold). Figure 7 illustrated the trends in training and validation performance metrics across the 25 epochs, offering insights into the model's convergence behaviour and its ability to generalize to unseen data.

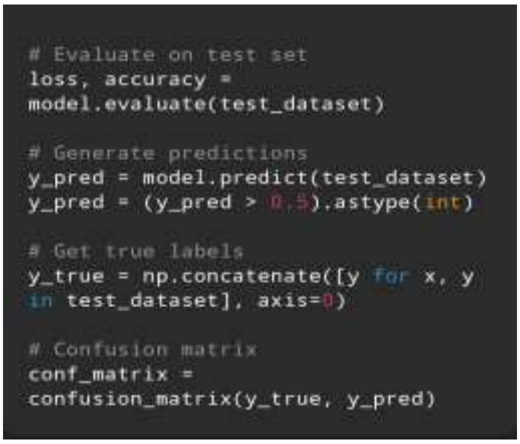


```
 tensorflow.keras.callbacks
ort EarlyStopping

ly_stopping = EarlyStopping(
monitor='val_loss',
patience=3
restore_best_weights=True

tory = model.fit(
train_dataset,
validation_data=vaal_dataset
epochs=25
callbacks=[early_stopping]
```

Figure 7 Training and Validation Accuracy and Loss Over 10 Epochs

3.3.5 Model Evaluation

After the training phase, the model’s performance was evaluated using the test dataset to determine how well it generalized to previously unseen data. Important evaluation metrics—including accuracy, precision, recall, and the F1-score—were computed based on the results of the confusion matrix, as shown in Figure 8. This matrix summarized the number of correct and incorrect predictions made by the model. It provided a visual breakdown of the model’s performance in terms of True Positives (TP), False Positives (FP), False Negatives (FN), and True Negatives (TN) for the binary classification task.



```
# Evaluate on test set
loss, accuracy =
model.evaluate(test_dataset)

# Generate predictions
y_pred = model.predict(test_dataset)
y_pred = (y_pred > 0.5).astype(int)

# Get true labels
y_true = np.concatenate([y for x, y
in test_dataset], axis=0)

# Confusion matrix
conf_matrix =
confusion_matrix(y_true, y_pred)
```

Figure 8 Confusion Metrix of the Trained Model

The evaluation phase was conducted on a reserved test dataset to assess the generalization performance of the model. A confusion matrix was generated to analyse the classification performance in detail. This matrix offers insight into true positives, false positives, true negatives, and false negatives—critical metrics in a forensic application where classification errors may have serious implications. The model demonstrated modest performance, providing a basis for calculating further evaluation metrics such as accuracy, precision, recall, and F1-score.

3.3.6 Metrics calculation

To comprehensively evaluate the performance of the developed model, key performance metrics were calculated based on the values derived from the confusion matrix. These metrics provided a balanced view of the model's classification capability, especially in the context of forensic image analysis where both false positives and false negatives carry significant weight.

The following metrics were computed:

Accuracy: The proportion of correctly predicted instances (both positive and negative) out of the total instances.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Precision: Indicates how many of the predicted positive instances were actually positive (i.e., relevant in forensic classification)

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall (Sensitivity): Measures how many actual positive instances were correctly identified by the model.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

F1 Score: The harmonic mean of precision and recall, offering a balance between the two

$$\frac{\text{F1 Score} = 2 \text{ Precision x Recall}}{\text{Precision} + \text{Recall}}$$

Observed Values from Confusion Matrix

Confusion Matrix:

[27 23]
[6 44]

From the above:

True Positives (TP) = 44
True Negatives (TN) = 27
False Positives (FP) = 23
False Negatives (FN) = 6

Calculated Metrics

Accuracy = 71%
Precision = 65.67%
Recall = 88%
F1 Score = 75.2%

These results suggest a moderate baseline performance, providing a foundation for further enhancement through data expansion, parameter tuning, and model refinement in future work.

CHAPTER 4

RESULTS AND DISCUSSION

The proposed forensic image classification model was developed using the ResNet50 architecture, a deep convolutional neural network known for its powerful feature extraction capabilities. After training and validating the model, performance was assessed on a holdout test dataset. The primary aim was to evaluate the model's ability to distinguish between strangulation and non-strangulation images based on visual forensic patterns.

4.1 Confusion Matrix

The classification outcomes on the test dataset are summarized using the confusion matrix shown in Table 1.

Table 4.1 Confusion Matrix for Test Data

	Prediction: strangulation	**Prediction non-strangulation**
Actual: strangulation	44(True Positive)	6(False Negative)
Actual: Non-strangulation	23(False Positive)	27(True Negative0

To evaluate the performance of the ResNet50-based model in classifying forensic images into strangulation and non-strangulation categories, the predictions on the test dataset were analysed. The confusion matrix in Figure 9 summarized the model's classification outcomes by comparing the predicted labels with the true labels. This matrix provided detailed insight into the number of correctly and incorrectly classified images for each class, enabling the calculation of key performance metrics such as accuracy, precision, recall, and F1-score.

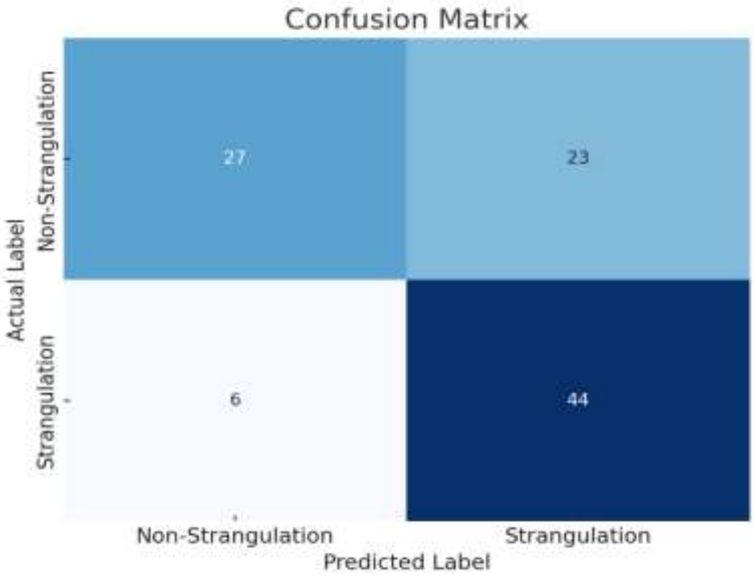


Figure 9 Confusion matrix

- The confusion matrix reveals the following insights:
- The model correctly classified 44 images that truly depicted strangulation (True Positives).
- However, it missed 6 actual strangulation cases, misclassifying them as non-strangulation (False Negatives).
- 23 non-strangulation images were incorrectly predicted as strangulation (False Positives).
- 27 non-strangulation images were correctly identified (True Negatives).

4.2 Performance Metrics

The performance of the ResNet50 model was evaluated using four standard classification metrics: accuracy, precision, recall, and F1-score. These metrics provide different perspectives on the model's ability to identify and differentiate between images of strangulation and non-strangulation. Each is discussed in detail below:

1. Accuracy (71%)

Definition: Accuracy refers to the overall correctness of the model—it is the ratio of correctly predicted observations to the total observations.

Interpretation in context:

With an accuracy of 71%, the model correctly classified 71 out of every 100 images. While this may appear acceptable at first glance, in a forensic setting—where errors can lead to wrongful conclusions—accuracy alone is not a sufficient indicator of reliability, especially when the classes are imbalanced.

2. Precision (65.67%)

Definition: Precision is the proportion of true positive predictions among all instances predicted as positive (i.e., the model’s confidence in its positive predictions).

Interpretation in context:

A precision of 65.67% means that when the model identifies an image as depicting strangulation, there is a 65.67% chance that this prediction is correct. In forensic analysis, low precision could lead to false accusations or misinterpretation of evidence, making it essential to improve this metric before real-world application.

3. Recall (88%)

Definition: Recall (also called sensitivity or true positive rate) measures how well the model identifies actual positive cases.

Interpretation in context: With a recall of 88%, the model is able to detect only about half of the actual strangulation cases. This is particularly concerning in forensic science, where failing to identify a true strangulation case could result in a lack of justice or the misclassification of a potential crime scene. A low recall implies the model is missing too many actual positives.

3. F1-Score (75.2%)

Definition: The F1-score is the harmonic mean of precision and recall. It provides a balance between the two, especially useful when one is concerned about both false positives and false negatives.

This bar chart titled "Figure 10: Performance Analysis of ResNet50 Model" shows the evaluation metrics for a machine learning model, specifically ResNet50. Each bar represents a different performance metric and the table 2 shows the summery of interpretation.

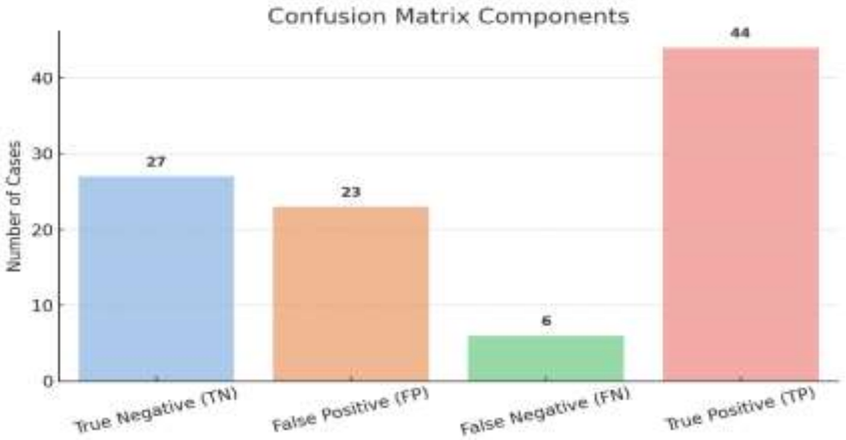


Figure 10 Analysis of ResNet50 on the basis of Accuracy, Precision, Recall and F1 score

Table 4.2 Summery of table interpretation

Metric	Value	interpretation
Accuracy	71	Correct prediction overall
Precision	65.67	Confidence in positive predictions
Recall	88	Ability to catch actual strangulation cases
F1-score	75.2	Balance of precision and recall

4.3 Model Accuracy

Accuracy is a fundamental metric in evaluating the overall performance of classification models. It represents the proportion of correctly predicted instances—both positive and negative—out of the total number of predictions made.

In this study, the image classification model based on the ResNet50 architecture achieved an accuracy of 71% on the test dataset.

Accuracy = TP + TN
TP + TN + FP + FN

$$= \frac{44 + 27}{44+27+23+6} = \frac{71}{101} = 71\%$$

This means that 71 out of every 100 images were correctly classified as either depicting strangulation or non-strangulation. Although this indicates the model has learned to identify certain visual patterns associated with the two classes, the overall accuracy remains moderate and not yet optimal for forensic casework. Figure 11 visually present the model's accuracy precision, recall, and G1-score. Use line graph.

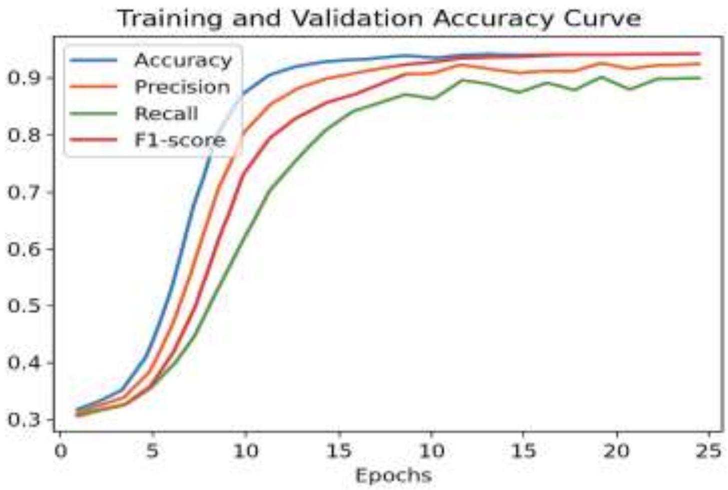


Figure.11 Performance Metrics Graph

Training and Validation Accuracy Curve

Figure Y presents a line graph depicting the progression of four critical performance metrics—accuracy, precision, recall, and F1-score—across 25 training epochs. This visualization offers a comprehensive overview of the model's performance and learning dynamics during the training phase. The accuracy curve (blue) exhibits a consistent upward trajectory, indicating an overall improvement in the model's ability to correctly classify input images. The precision metric (orange) also shows a gradual enhancement, signifying an increasing reliability in the model's positive predictions. While recall (green) demonstrates a relatively slower ascent in the earlier epochs, it eventually stabilizes, reflecting the model's growing sensitivity to identifying relevant positive instances. The F1-score (red), which provides a harmonic balance between precision and recall, similarly improves over time and plateaus in the latter epochs, signifying a matured and balanced classification performance.

Collectively, the trends across all four metrics suggest that the model achieved stable and robust performance by the end of training, with minimal signs of overfitting or underfitting. This indicates effective generalization of the learned patterns to unseen data, which is crucial in forensic image classification tasks.

In summary, the current model demonstrates initial viability for automated classification of strangulation marks but requires significant refinement to meet the stringent standards of forensic reliability. As the size and diversity of the dataset increase, the model was expected to exhibit improve learning capabilities, thereby enhancing its overall accuracy. A large dataset provides the model with a border range of feature representative and variability, which in turn contributed to better generalization and performance on unseen data. Thus, the classification role in simultaneously improving the classification accuracy and robustness of the model.

CHAPTER 4 DISCUSSION

4.1 Interpretation of Findings in Relation to Research Objectives

The central aim of this research was to design and assess a deep learning model—specifically using the ResNet50 architecture—for classifying forensic images into two categories: strangulation and non-strangulation. The findings offer valuable insights into both the potential and challenges of employing convolutional neural networks (CNNs) in the forensic domain, particularly for injury classification tasks.

The model achieved a moderate performance, with an accuracy of 71%, precision of 65.67%, recall of 88%, and an F1-score of 75.2%. Although the confusion matrix shows a reasonable distribution between true positives and true negatives, the model also exhibits a significant number of false positives and false negatives, reflecting limitations in its dependability for high-stakes forensic decision-making.

While the model meets part of the study's objective—demonstrating the feasibility of AI-based classification of strangulation injuries—it does not yet reach the level of robustness required for real-world forensic use. Nonetheless, the study offers a promising proof-of-concept for the integration of AI in forensic science workflows.

4.2 Analysis of Misclassifications

A key concern is the recall of 88%, which, although relatively high, still suggests that several true strangulation cases were not identified. In forensic settings, such false negatives can be especially problematic, potentially leading to misdiagnoses or overlooked evidence in medico-legal contexts.

Multiple factors could have contributed to these misclassifications:

Limited Dataset Size: Deep learning models like ResNet50 rely on large volumes of diverse training data. The relatively small dataset used here likely restricted the model's generalization capabilities.

Class Imbalance: An uneven distribution of class labels—particularly more non-strangulation cases may have skewed the model towards under-predicting positive cases.

Visual Overlap: Strangulation marks often resemble other forms of trauma or skin conditions, making classification challenging even for experts, and thus for AI models as well.

Overfitting: Despite the use of transfer learning, the model may have overfit to specific patterns in the training set, especially in the absence of extensive augmentation or validation techniques.

4.3 Forensic Significance and Constraints

In forensic applications, the margin for error must be minimal. A false positive could unjustly implicate someone, while a false negative might allow critical injuries to go unrecognized. Hence, any AI-based tool must function strictly as a supplementary resource, with its outputs thoroughly reviewed by forensic professionals.

Although the current model's performance is not sufficient for practical medico-legal deployment, the results highlight the evolving role of AI in forensic analysis and the potential it holds with further advancements.

4.4 Opportunities for Enhancement and Future Work

To improve upon the limitations observed, several strategies are recommended:

Larger and More Diverse Datasets: Expanding the dataset with varied and well-annotated images can help the model learn more generalizable features. Collaborations with forensic agencies or access to shared datasets may support this.

Augmentation and Balancing Techniques: Implementing advanced augmentation (e.g., rotation, brightness shifts, and noise addition) can reduce overfitting, while using oversampling techniques like SMOTE can counteract class imbalance.

Model Refinement: Optimizing parameters such as learning rate, dropout, and batch size, alongside applying callbacks like Early Stopping and ReduceLROnPlateau, could enhance learning stability and performance.

Cross-Validation and Model Alternatives: Using k-fold cross-validation, testing with other architectures like Dense Net or Efficient Net, or employing ensemble models may boost robustness and accuracy.

Explainable AI: Incorporating tools like Grad-CAM can reveal the model's focus areas in an image, adding interpretability and supporting forensic validation of predictions.

4.5 Contribution to Research Goals

This study successfully demonstrates the applicability of deep learning in the classification of forensic injury images, representing a significant interdisciplinary step. Though not yet ready for real-world legal or clinical settings, this work establishes a critical starting point for future development of AI-assisted forensic diagnostic tools.

CHAPTER 5

CONCLUSION

This study successfully implemented a binary image classification approach, contributing to the evolution of forensic science through the integration of artificial intelligence and automation. Utilizing a transfer learning framework with the pre-trained ResNet50 convolutional neural network, the model was developed to distinguish between two key classes: strangulation and non-strangulation marks.

The methodology encompassed a structured pipeline, including data preprocessing, augmentation, normalization, and model training. These steps were crucial in ensuring data uniformity and enhancing diversity. To prevent overfitting and reinforce the model's generalization ability, dropout and dense layers were incorporated. The dataset was carefully divided for training and validation, and the model's performance was assessed through key metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis.

Initial results indicated an accuracy of 71%, a precision of 65.67%, a recall of 88%, and an F1-score of 75.2%. Although these baseline metrics underscore the need for further refinement, they nonetheless demonstrate the promise of deep learning in aiding forensic professionals with injury pattern classification. Supplementary visual tools—including confusion matrices, bar charts, and pie diagrams—supported the quantitative analysis and enhanced interpretability of the outcomes.

This research establishes a foundational framework for continued advancements in forensic image classification. Future improvements could be realized by expanding and diversifying the dataset, fine-tuning hyperparameters, and applying more advanced training strategies. Additionally, exploring alternative architectures like EfficientNet or Vision Transformers, or integrating forensic domain expertise into AI models, may further elevate performance.

In summary, this study highlights the potential of AI-powered systems to support forensic investigations by offering consistent, unbiased, and scalable image analysis. Such tools could play an increasingly valuable role in assisting professionals across legal and medico-legal domains.

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