Automated Detection of Intracranial Hemorrhage using Artificial Intelligence and Deep Learning Techniques

Thesis submitted in fulfillment of the requirements for the degree **Postgraduate Diploma in Data Analytics** at The Independent Institute of Education, Varsity College**.**

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Declaration:

I hereby declare that the **research report** submitted for the **Postgraduate Diploma in Data Analytics** to The Independent Institute of Education (The IIE) is my own work and has not previously been submitted to another University or Higher Education Institution for a postgraduate qualification.

Signature Date___07/11/2023___

Abstract:

Background:

The field of haemorrhage detection has undergone a transformative revolution in recent years, thanks to the advent of artificial intelligence (AI) and deep learning techniques. Intracranial haemorrhages, significant contributors to global morbidity and mortality, demand swift and accurate diagnosis and management. Traditional diagnosis, reliant on the expertise of radiologists, can introduce interpretation discrepancies and diagnostic delays. In contrast, AI and deep learning have ushered in a new era, offering automated detection with enhanced accuracy, efficiency, and objectivity. This study investigates the efficacy of AI and deep learning in automating the identification of intracranial haemorrhages, aiming to develop a dependable system for recognizing and localizing disorders in medical images, such as computed tomography (CT) scans and magnetic resonance imaging (MRI) scans. The research's significance lies in its potential to revolutionize clinical workflows, providing healthcare practitioners with tools for faster and more accurate diagnosis, leading to increased productivity, reduced diagnostic errors, and prompt treatments. Consequently, this research has the potential to profoundly impact patient outcomes, reduce the burden on healthcare systems, and save lives.

Methodology:
The research employs the "RSNA Intracranial Haemorrhage Detection" competition dataset from Kaggle, created in collaboration with the Radiological Society of North America (RSNA®) and esteemed research institutions. This dataset serves as the foundation for investigating automated intracranial haemorrhage detection, harnessing AI, and deep learning. Our study evaluates AI models known as deep learning architecture models, specifically RESNET, DENSE, and INCEPT, in detecting and localizing intracranial haemorrhages, aiming to provide a comparative analysis of their performance. [link: Kaggle Dataset]

Findings:
Our findings reveal essential insights into the integration of AI and deep learning in intracranial haemorrhage detection. Notable outcomes include the epoch testing and its visualisation, which illustrates the progression of model performance during training. Architectural performance analysis demonstrates the accuracy and efficacy of RESNET, DENSE, and INCEPT models, with associated metrics highlighting their respective strengths and weaknesses.

Interpretation:
AI and deep learning technologies offer a substantial enhancement in the accuracy of intracranial haemorrhage detection. However, it is crucial to view these technologies as complementary tools rather than replacements for radiologists and medical practitioners' expertise.

Conclusions and Recommendations:
This research concludes that AI and deep learning can significantly enhance the accuracy of intracranial haemorrhage detection. Medical practitioners and researchers should consider the suitability of architectural backbones based on specific diagnostic requirements. Future research should address and focus on real-time clinical integration and the development of adaptive architectures tailored to medical imaging challenges.

Scholarly Contribution:
This study enriches the scholarly discourse by emphasizing the pivotal role of AI and deep learning in revolutionizing intracranial haemorrhage detection. The comprehensive assessment of architectural backbones provides valuable insights for the academic community.

Limitations and Future Research:
This research acknowledges its limitations, including the need for further potential variations in real-world clinical settings. Future research should explore the intricacies of AI models and their real-time integration in clinical environments, advancing the field of medical diagnostics and patient care.

In summary, this thesis demonstrates the transformative potential of AI and deep learning in intracranial haemorrhage detection, offering a promising path toward more accurate and efficient medical diagnostics.

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Conceptualization:

1. **Artificial Intelligence (AI):** Intelligent computer systems capable of tasks requiring human intellect are being developed utilising techniques such as machine learning, natural language processing, visual processing, and robotics (Burns, Laskowski and Tucci, 2023).

2. **Machine learning:** The creation of algorithms and models allowing computers to learn from data, make estimations, and take actions based on patterns is a branch of artificial intelligence (Ibm.com, 2016).

3. **Intracranial Haemorrhages**: Intracranial haemorrhages are characterized by bleeding within the skull or brain tissue. This condition is a severe medical disorder that can lead to neurological problems and potentially fatal consequences. Various types of intracranial haemorrhages exist, each with its unique characteristics (Wright, 2008).

4. **Computed Tomography (CT) Scans**: Computed tomography scans are diagnostic imaging procedures that use X-rays to create cross-sectional images of the body, including the brain. CT scans are commonly employed to detect intracranial haemorrhages (Hopkinsmedicine.org, 2023).

5. **Magnetic Resonance Imaging (MRI) Scans:** Magnetic resonance imaging is a medical imaging technique that uses magnetic fields and radio waves to generate detailed images of the body's internal structures, including the brain. MRI scans are valuable for detecting intracranial haemorrhages (National Institute of Biomedical Imaging and Bioengineering, 2023).

6. **Medical imaging:** Techniques for visualising interior body structures and processes, such as X-rays, CT scans, MRI, and ultrasound, can help in evaluation, planning of treatment, and monitoring of medical disorders (Brush, 2019).

7. **Deep learning:** A subset of machine learning that use neural networks to learn and extract complex patterns from input, allowing for tasks such as image recognition and natural language processing (Ibm.com, 2015).

Key Terms:

Artificial Intelligence, Machine Learning, Neural Networks, Computed Tomography, Intracranial Haemorrhages.

Abbreviations:

1. **CAD:** Computer Assisted Detection

2. **CT:** Computed Tomography

3. **MRI:** Magnetic Resonance Imaging

Acknowledgements:

I would like to commence this section by dedicating the entirety of this body of research to my beloved mother, Gulshad Begum Cassim, whose memory serves as both a driving force for my academic journey and my greatest inspiration. The strength, love, wisdom, and resilience that she has bestowed upon me continue to shape my life and pursuits.

My mother has passed on due to intracranial haemorrhages as caused by aneurysms, the very ailment that became the focus of this research. Her battle was a testament to her courage and unwavering spirit. Her memory fuels my determination to contribute to the field of medical analysis aided by technology and the understanding and treatment of this condition, in the hopes of increased awareness and that others may be benefited by the positive results of early detection and treatment.

I would also like to express my appreciation to my academic advisor, Zahra Bulbulia, for their invaluable guidance, mentorship, and expertise that have shaped this research. Their support and encouragement have been instrumental in my academic development.

To the participants who generously shared their experiences, data, and insights for this study, I extend my heartfelt thanks. Your contributions have been essential in advancing our understanding of intracranial haemorrhages.

This research is dedicated to the memory of my mother, and to every individual whose life has been affected by intracranial haemorrhages. May this work contribute to a future where the impact of intracranial haemorrhages is minimized, and where families are spared the pain of loss that my own has experienced.

In loving memory of my mother.

Mohamed Sohail Rajab

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Chapter 1: Introduction

Artificial intelligence (AI) and deep learning techniques have revolutionized the area of medical imaging in recent years, enabling automated identification and diagnosis of a variety of clinical disorders. Intracranial haemorrhages are important sources of morbidity and mortality globally and require immediate diagnosis and management. The diagnosis of these disorders in a timely and accurate manner is critical for providing appropriate medical treatment and improving patient outcomes. Detection and diagnosis of cerebral haemorrhages have traditionally depended primarily on radiologists' knowledge and experience, potentially leading to discrepancies in interpretation and delays in diagnosis. Recent advances in AI and deep learning, on the other hand, have opened new opportunities for automating the detection process and improving accuracy, efficiency, and objectivity. The **purpose** of this body of research is to investigate the efficacy of AI and deep learning approaches in automating the identification of intracranial haemorrhages. This study aims to develop and test a robust and dependable system capable of reliably recognising and localising various disorders inside medical pictures such as computed tomography (CT) scans and magnetic resonance imaging (MRI) scans by utilising the capabilities of machine learning techniques.

The **relevance** of this research lies in its potential to revolutionise clinical workflow by providing new tools to healthcare practitioners for faster and more accurate diagnosis. Healthcare professionals can profit from increased productivity, decreased diagnostic mistakes, and prompt treatments by automating the detection process. This, in turn, has the potential to have a significant influence on patient outcomes, potentially saving lives and decreasing the strain on healthcare systems. To achieve the goals of this research, a thorough evaluation of the available literature on automated detection of intracranial haemorrhages will be performed. The methodology, algorithms, and performance indicators used in prior research will be critically examined in this study, noting their strengths, shortcomings, and potential areas for development. Using state-of-the-art deep learning techniques and image analysis algorithms, the research will next focus on designing and assessing an AI-powered system for automatic detection. Overall, the goal of this research project aims to add to the expanding area of AI-assisted medical imaging by solving the essential difficulty of identifying cerebral haemorrhages. The effective adoption of an automated detection system might have far-reaching repercussions in healthcare, allowing for early intervention and better patient outcomes. We hope to expand existing understanding, approaches, and technologies linked to the automated identification of these life-threatening illnesses through this research, thereby helping patients, healthcare providers, and society.

What is AI? AI is an expanding field of computer science and technology aimed at developing intelligent systems capable of doing activities that would normally need human intelligence (Burns, Laskowski and Tucci, 2023). It includes several subfields, including machine learning, natural language processing, computer vision, and robotics. AI systems are intended to analyse massive volumes of data, learn patterns and rules, make sound judgements, and adapt to changing conditions. They process information, reason, and solve complicated issues using techniques like as neural networks, algorithms, and statistical models. AI has a wide range of applications in areas such as healthcare, banking, transportation, and recreation, and its potential influence on society varies from efficiency and automation improvements to ethical concerns and the future of labour.

What is deep learning? Deep learning is a subfield of artificial intelligence that focuses on training artificial neural networks with multiple layers to learn and extract complex patterns and representations from data (Ibm.com, 2016). By utilizing hierarchical architectures and large amounts of labelled data, deep learning models can automatically discover and understand intricate features at different levels of abstraction. These models learn iteratively by adjusting the weights and biases of the network based on observed errors, enabling them to make increasingly accurate predictions and classifications. Deep learning has revolutionized various domains, including computer vision, natural language processing, and speech recognition, and has fuelled advancements in areas such as autonomous systems, medical diagnostics, and recommendation systems, contributing to the ongoing progress of AI technologies.

What are Intracranial Haemorrhages?

Intracranial haemorrhages are defined as bleeding within the skull or brain tissue (Clinic, 2020). It is a serious medical disorder that can result in severe neurological problems and potentially fatal effects. Intracranial haemorrhages are classified into numerous types:

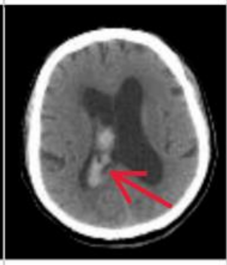
	Intraparenchymal	Intraventricular	Subarachnoid	Subdural	Epidural
Location	Inside of the brain	Inside of the ventricle	Between the arachnoid and the pia mater	Between the Dura and the arachnoid	Between the dura and the skull
Imaging					
Mechanism	High blood pressure, trauma, arteriovenous malformation, tumor, etc	Can be associated with both intraparenchymal and subarachnoid hemorrhages	Rupture of aneurysms or arteriovenous malformations or trauma	Trauma	Trauma or after surgery
Source	Arterial or venous	Arterial or venous	Predominantly arterial	Venous (bridging veins)	Arterial
Shape	Typically rounded	Conforms to ventricular shape	Tracks along the sulci and fissures	Crescent	Lentiform
Presentation	Acute (sudden onset of headache, nausea, vomiting)	Acute (sudden onset of headache, nausea, vomiting)	Acute (worst headache of life)	May be insidious (worsening headache)	Acute (skull fracture and altered mental status)

Figure 1.1: Haemorrhage Types

Image from RSNA Intracranial Haemorrhage Detection Kaggle Competition (Kaggle.com, 2023)

Intraparenchymal haemorrhage: the presence of bleeding within the brain tissue itself is referred to as intraparenchymal haemorrhage. This syndrome is commonly caused by several causes, including uncontrolled high blood pressure, head injuries, or underlying vascular abnormalities. The bleeding can cause localised brain injury, resulting in a variety of neurological symptoms. Immediate medical attention is required to avoid more serious outcomes and to address the underlying causes of this type of haemorrhage. Depending on the conditions and severity of the intraparenchymal haemorrhage, treatment may include surgery, medication, or other therapeutic techniques (Toledano and Fugate, 2017).

Intraventricular Haemorrhage: is a medical disorder characterised by bleeding within the ventricular system of the brain, which is made up of four fluid-filled cavities. IVH is most common in premature infants or people with medical disorders, and it is frequently connected with other brain-related complications. The bleeding can cause an accumulation of blood in the ventricles of the brain, thereby increasing intracranial pressure and interfering with the circulation of cerebrospinal fluid. IVH is a dangerous illness that necessitates immediate medical attention and can result in neurological and developmental issues, particularly in premature infants (Hopkinsmedicine.org, 2020).

Intracranial haemorrhages can cause increased pressure within the skull, which can result in brain compression, ischemia (a lack of blood flow to the brain), and neurological impairments. Prompt identification and response are critical for properly treating intracranial haemorrhages.

Subarachnoid Haemorrhage: a distinctive form of brain bleeding, involves the presence of blood in the space between the arachnoid membrane and the delicate pia mater that envelops the brain. This type of haemorrhage is often triggered by a ruptured cerebral aneurysm or head trauma. Subarachnoid haemorrhages can result in sudden, severe headaches and other neurological symptoms. Prompt medical attention is crucial to address the underlying cause and prevent complications. Treatment may include neurosurgical procedures or endovascular techniques, depending on the patient's condition (Hopkinsmedicine.org, 2019).

Subdural Haemorrhage: is characterized by bleeding between the dura mater and the arachnoid membrane, which forms the middle layer of the brain's protective covering. Unlike epidural haemorrhages, subdural bleeding can occur because of head trauma or be linked to underlying medical conditions and disorders. The condition can be acute or chronic, with symptoms varying in severity. Management may involve surgical drainage or other medical interventions, depending on the specific case (Cedars-sinai.org, 2022).

Epidural Haemorrhage: a type of intracranial bleeding, occurs when blood accumulates between the skull and the outer layer of the brain, known as the dura mater. This specific haemorrhage is primarily associated with head trauma and injury, often resulting from accidents or falls. The increased pressure within the epidural space can compress the brain, leading to a range of symptoms. Swift diagnosis and surgical intervention are crucial for relieving pressure and preventing further neurological damage (Uclahealth.org, 2023).

An **aneurysm** is a weakened and bulging region of a blood vessel's lining (Mayo Clinic, 2023). This weakening happens in the blood arteries of the brain in the context of intracranial aneurysms. Haemorrhages are often a direct result of a ruptured o untreated aneurysm.

Aneurysms are frequently categorised according to their form and size:

Saccular or Berry Aneurysms: The most common form of aneurysm, with a rounded or sac-like structure. They are frequently tiny and occur near artery branching locations.

Fusiform Aneurysms: These are elongated aneurysms that involve the full circumference of the blood artery. They are less prevalent than saccular aneurysms.

Giant Aneurysms: These are aneurysms that are greater than 2.5 cm in diameter and are more likely to burst. They necessitate specialised management strategies.

Mycotic aneurysm: This form of aneurysm is brought about by an infection. When an infection affects the arteries in the brain, it might damage the arterial wall. This can lead to the formation of an aneurysm.

Although the specific origin of aneurysm formation is unknown, some variables such as genetic susceptibility, persistent hypertension, smoking, and certain connective tissue diseases may all play a role. Aneurysms can go unnoticed for a long time, but if they burst, they can create a subarachnoid haemorrhage, which can cause a severe headache, loss of consciousness, or neurological impairments.

Aneurysm diagnosis and treatment are critical for avoiding rupture and other consequences, such as intracranial haemorrhages. Aneurysms are often identified and assessed using imaging techniques such as computed tomography angiography (CTA) and magnetic resonance angiography (MRA).

Understanding the nature, causes, and treatment of intracranial haemorrhages and aneurysms is critical for the development of automated detection techniques based on artificial intelligence and deep learning, as it lays the groundwork for accurately identifying and diagnosing these critical conditions.

Research Questions:

1. What is the diagnostic accuracy of the AI model in detecting intracranial haemorrhages?
2. How does the integration of deep learning techniques impact the automated detection system for intracranial haemorrhages?

Hypothesis:
Null Hypothesis (H0): Artificial intelligence is unable to accurately detect and localize intracranial haemorrhages.
Alternative Hypothesis (H1): Artificial intelligence models can precisely detect and localize intracranial haemorrhages.
Hypothesis 2:

Null Hypothesis (H0): The utilization of artificial intelligence and deep learning techniques, as a tool, does not significantly improve the accuracy of automated intracranial haemorrhage and aneurysm identification compared to human specialists.
Alternative Hypothesis (H1): The use of artificial intelligence and deep learning techniques, as a tool, substantially enhances the accuracy of automated intracranial haemorrhage and aneurysm identification compared to human specialists.

Chapter 2: Literature review

This literature review aims to provide a comprehensive overview of research studies focusing on the automated detection of intracranial haemorrhages using artificial intelligence (AI) and deep learning techniques. Intracranial haemorrhages are critical conditions that require prompt diagnosis and treatment to prevent severe consequences. The integration of AI and deep learning algorithms has shown great potential in improving the accuracy and efficiency of detection, enabling early intervention and improved patient outcomes. This review synthesizes the current state of research, discusses the methodologies employed, highlights challenges, and suggests future directions in this rapidly evolving field. Some research papers we included:

Pennig, L., Hoyer, U. C. I., Krauskopf, A., Shahzad, R., Jünger, S. T., Thiele, F., Laukamp, K. R., Grunz, J. P., Perkuhn, M., Schlamann, M., Kabbasch, C., Borggrefe, J., & Goertz, L. (2021) conducted a study with the title "Deep learning assistance increases the detection sensitivity of radiologists for secondary intracranial aneurysms in subarachnoid hemorrhage". In their research they conducted studies to evaluate whether deep learning models (DLM) can increase the detection rate, by radiologists, of intracranial aneurysms with the aid of CT (Computed tomography) angiography (CTA) in aneurysmal subarachnoid haemorrhage (aSAH). In this study the researchers investigated the application of DLMs in boosting radiologists' detection sensitivity for cerebral aneurysms on CT angiography (CTA) in aSAH. The researchers used three distinct DLMs that were trained on CTA datasets of 68 aSAH patients with 79 aneurysms. These models' outputs were blended using ensemble learning to form the DLM-Ens. An independent test set of 104 aSAH patients with 126 aneurysms was employed to evaluate the performance of the DLM-Ens. Using CTA and digital subtraction angiography imaging, two radiologists and one neurosurgeon reached an agreement on these aneurysms. The test set's CTA images were then shown to three blinded radiologists with varied years of diagnostic neuroradiology expertise. The finding revealed that the DLM-Ens detection rate was equivalent to the detection rate of the radiologists, with results all above 85% for 3 different cases. The detection rate dramatically increased when the radiologists made use of the DLM tools to above 95%. The findings of this study highlighted the potential of DLMs in improving the overall detection sensitivity of radiologists on intracranial aneurysms in aSAH. Pennig et al., (2021) outlined its value in accurate diagnosis which in turn would optimize patient treatment. The findings from this study greatly contribute to the ever-growing body of literature which support the field of deep learning and its benefits on medical diagnosis and management. Deep learning research and improvements show potential for improving the efficacy and accuracy of aneurysm identification, eventually helping both patients and medical professionals.

Shahzad, R., Pennig, L., Goertz, L., Thiele, F., Kabbasch, C., Schlamann, M., Krischek, B., Maintz, D., Perkuhn, M., & Borggrefe, J. (2020) conducted a study with the title "Fully automated detection and segmentation of intracranial aneurysms in subarachnoid haemorrhage on CTA using deep learning".

Shahzad et al., (2020) highlight that previous research employed CTA and time-of-flight magnetic resonance angiography (TOF-MRA) to detect unruptured intracranial aneurysms (UIAs). However, research examining the efficacy of deep learning models (DLMs) for identifying and segmenting aneurysms in aSAH patients are few. Given the difficulties in finding and diagnosing aneurysms in this group, the development of a DLM for aSAH patients may be beneficial. The goal of their study was to create and test a DLM for automated identification and segmentation of aneurysms on CTA in aSAH patients. The study used an independent test set to evaluate the DLM's performance in terms of aneurysm size, location, and bleeding severity. The study comprised 68 patients with aSAH who underwent CTA for aneurysm identification and was completed retrospectively at a single centre. Using five-fold cross-validation, three separate DLMs were trained, and their outputs were blended using ensemble learning. The DLM's performance was assessed on an independent test group of 185 patients with aSAH. Two readers (neurosurgeon and radiologist) manually segmented aneurysms to establish the reference standard. From their research they found that The DLM has a detection sensitivity of 87% for aneurysms bigger than 30 mm^3 on the test set, with a false positive (FP) rate of 0.42 per scan. When compared to the reference standard, automatic segmentations had a median dice similarity coefficient (DSC) of 0.80. The location of the aneurysm and the intensity of the bleeding had no effect on detection sensitivity or segmentation performance. The DLM has a sensitivity of 96% for aneurysms greater than 100 mm^3, with a DSC of 0.87 and FPs per scan of 0.14. The study indicated that, regardless of cerebral circulation or bleeding severity, the suggested DLM can identify and segment aneurysms bigger than 30 mm^3 in patients with aSAH with excellent sensitivity. The DLM demonstrated a low proportion of false positive results and performed well in identifying bigger aneurysms. The DLM has the potential to help treating doctors by automating the identification and segmentation of aneurysms. Although the study featured a retrospective methodology and contained scans from a single centre, limiting the findings' generalizability. Future multi-centre research should look at evaluating the DLM on CTA images obtained from different scanners and procedures. Aneurysms that had previously been treated were not included, necessitating further evaluation of the DLM's effectiveness in these patients. In conclusion the study created and tested a DLM for automated identification and segmentation of aneurysms in aSAH patients. The DLM detected aneurysms greater than 30 mm3 with good sensitivity.

Shi, Z., Hu, B., Schoepf, U.J., Savage, R.H., Dargis, D.M., Pan, C.W., Li, X.L., Ni, Q.Q., Lu, G.M., & Zhang, L.J. (2020) have outlined the problems and prospects of artificial intelligence use in aneurysm treatment. Unruptured cerebral aneurysms

continue to be a serious public health issue, affecting between 3%-7% of the general population. Although CTA and MRA (Magnetic resonance angiography) are the favoured procedures for detecting aneurysms, the growing demand for imaging investigations has resulted in a dearth of competent radiologists. The increased pressure on physicians might lead to doubt and mistakes in diagnosis and judgements. Shi et al., (2020) mention that the majority of nontraumatic subarachnoid haemorrhage cases are caused by aneurysms, which pose significant morbidity and death concerns. The limits of endovascular and surgical therapies emphasise the need for risk factor detection and prediction models for aneurysm inception, growth, rupture, and intervention assessment. AI has been used for automated morphologic computation, rupture risk categorization, and outcome prediction, and it has demonstrated additional utility in these domains. The researchers also mention that while artificial intelligence has been used in several parts of aneurysm care, there are limitations and obstacles that must be addressed. Model validation processes need additional attention, particularly in real-world case studies. The time necessary to train deep learning (DL) models, as well as the cost-effectiveness of imaging data storage and processing, should also be addressed. The use of limited and institution-specific datasets for training and validation frequently results in algorithm overfitting, requiring external validation across populations and institutions. They mention that comprehensive clinical performance and generalizability validations are required for wider application in real-world practise. AI solutions with humans in the loop and prospective research can improve AI's dependability and clinical decision-making skills.in conclusion Shi et al., (2020) states that deep learning, in particular, offers promise in assisting in the management of cerebral aneurysms. It has exhibited detection, rupture risk assessment, therapy triaging, and treatment result prediction capabilities. Even though problems such as advanced network architectures and strong validation methods persist, AI has the ability to handle these concerns in a patient-centric manner and enhance aneurysm care. This research was funded by funding from the National Natural Science Foundation of China's Key Projects and the National Key Research and Development Programme of China.

Seyam, M., Weikert, T., Sauter, A., Brehm, A., Psychogios, M.-N., Blackham, K. A., (2022) have published a research paper with the title “Utilization of Artificial Intelligence–based Intracranial Hemorrhage Detection on Emergent Noncontrast CT Images in Clinical Workflow”. Seyam et al., (2022) have conducted a study that compared the AI-based detection tool's diagnostic performance to that of pre-AI implementation. The radiography reports, which were regarded as the truth, were incorporated in the analysis. Using ICH-related keywords, a total of 4,450 CT exams were found. The diagnostic performance was analysed, as well as several process parameters such as report turnaround time, communication time of a discovery, consultation time with another speciality, and emergency department turnaround time. The AI-based detection method has a diagnostic accuracy of 93.0% for ICH (Intracranial Haemorrhage) diagnosis, 87.2% sensitivity, and 97.8% negative predictive value. Specific subtypes of ICH, such as subdural haemorrhage (69.2%) and acute subarachnoid haemorrhage (77.4%), have decreased detection rates. Postoperative and postischemic abnormalities, artefacts, and tumours were among the false-positive results. Despite improvements in workflow metrics following AI deployment, further work is needed to optimise the workflow across the board. The study emphasised the significance of establishing a clear framework and understanding the limitations of AI technologies. While artificial intelligence (AI) has demonstrated promising outcomes in clinical care, its dependability is greatly dependent on the deployment environment. To guarantee their trustworthy and successful application in clinical practise, the study indicated that AI technologies should be incorporated into a standardised framework and post interpretative processes should be addressed. In conclusion of this study, it can be noted that the use of an AI-based detection tool for ICH on non-contrast CT images exhibited adequate diagnostic performance and the potential for workflow optimisation. However, specific subtypes of ICH and acute care applications may create issues, and further efforts are required to optimise the process and overcome deployment environment limits.

Geng, C., Wei, X., Huang, L., Li, Y., Li, Q., Dai, Y., & Geng, D. (2023) have put together a research paper with the title "Automated computer-assisted detection system for cerebral aneurysms in time-of-flight magnetic resonance angiography using fully convolutional network". Chen et al., (2020) stresses the importance of early identification of cerebral aneurysms and the possibility of a computer-assisted detection (CAD) system to assist medical professionals in accurate diagnosis. It discusses the limits of 3D convolutional neural networks (CNN) for recognising blood vessels and the usage of contrast-unenhanced time-of-flight magnetic resonance angiography (TOF-MRA) as a regularly utilised screening approach. They show usefulness of fully convolutional networks (FCNs) for picture segmentation and lesion identification in medical imaging, as is the application of TOF-MRA as a non-invasive screening tool. Previous research on employing deep neural networks for cerebral aneurysm diagnosis is also presented, with an emphasis on approaches that use 2D CNN networks or hand-engineered features. Several investigations, including those of Nakao et al., Ueda et al., and Hanaoka et al., are listed, with various degrees of sensitivity and false-positive rates. FCNs' use in medical imaging and lesion identification is also highlighted. The findings section summarises the CAD system's performance based on the assessment measures. It emphasises the sensitivity attained in the internal test dataset's fivefold cross-validation and the detection efficiency on the external test dataset. The impact of aneurysm size, hypertension, and location within the brain is explored, and the system's overall effectiveness is assessed across several subgroups. To offer visual context and assist the discussion, the figures in the body of research exhibit instances of volume-rendered pictures, including detected and undetected aneurysms.

Kundisch, A., Hönning, A., Mutze, S., Kreissl, L., Spohn, F., Lemcke, J., Sitz, M., Sparenberg, P. and Goelz, L. (2021) address the challenge of detecting intracranial haemorrhage on head computed tomography scans at high-volume centres, particularly in the setting of Level I trauma centres with teleradiology services. In a retrospective multi-centre cohort study of 4,946 HCT scans, the researchers discovered that supplementing human experience with an AI algorithm resulted in a 12.2% increase in ICH detection. The AI algorithm incorrectly predicted 1.9% of instances, owing to factors such as calcifications and beam-hardening artefacts. The study also emphasised the prevalent location of missing ICHs in the subarachnoid space and under the calvaria, as well as the effect of off-hours timing on radiology report accuracy. This study highlights AI's promising role in improving ICH detection, particularly in high-volume centres using teleradiology services and during on-call duty.

Overall, the study gives a thorough summary, including background information, relevant work, methods, findings, and commentary. It emphasises the need of establishing a CAD system for detecting cerebral aneurysms and describes the technique employed in this study, as well as its performance evaluation.
The five research articles offered are concerned with the identification and segmentation of cerebral haemorrhages and aneurysms using deep learning and artificial intelligence (AI) approaches. They emphasise the potential of these technologies to improve diagnostic accuracy and efficiency in this sector. These technologies have demonstrated promising outcomes in terms of enhancing diagnosis accuracy and efficiency, which will eventually benefit patients and medical personnel. However, further study is required to address issues such as validation, generalizability, process optimisation, and identification of specific subtypes.

A Conceptual Review and Parallels:
In the contemporary landscape, a conceptual exploration of AI and deep learning techniques in the detection of intracranial haemorrhages unveils a profound paradigm shift in the realm of medical diagnostics. AI models, empowered by deep learning, have showcased the capability to surpass traditional radiological approaches in terms of rapidity, precision, and consistency. The amalgamation of these technologies resonates with the dawn of a new era in medical imaging, offering the potential for augmented diagnostic prowess and timely interventions. Drawing parallels between these concepts, it becomes evident that AI's adeptness at deciphering intricate patterns within medical images harmonizes with the quest for more precise and expeditious intracranial haemorrhage detection.

Analysis and Synthesis of Literature:
A comprehensive analysis and synthesis of the literature unveil a growing consensus regarding the transformative potential of AI and deep learning in revolutionizing intracranial haemorrhage diagnosis. The studies encompassed in this discourse depict an evolution in AI models, transitioning from conventional convolutional neural networks to more advanced architectures. These models, often bolstered by ensemble learning, exhibit an enhanced capacity to discern and delineate intracranial aneurysms and haemorrhages with remarkable accuracy. This synthesis reaffirms the significant progress made in the development of AI-based diagnostic tools for the medical community.

Identifying Gaps and Issues:
While the present body of literature showcases commendable strides in intracranial haemorrhage detection, it also brings to the fore several noteworthy gaps and

unresolved challenges. For instance, specific subtypes of intracranial haemorrhages, such as subdural haemorrhage and acute subarachnoid haemorrhage, still present formidable detection challenges for AI models. Furthermore, a predominant reliance on retrospective datasets from single centres raises concerns about the application of these models to diverse populations and imaging procedures. Additionally, there is a persistent need for robust model validation processes and external validation across different healthcare settings. Addressing these gaps and issues is of paramount importance in further enhancing the reliability and practicality of AI-driven intracranial haemorrhage detection.

Logical Narrative:

The literature reviewed here is presented in a logical and coherent narrative. It commences with foundational studies by Pennig et al. (2021) and Shahzad et al. (2020), which lay the groundwork for the integration of AI models in intracranial haemorrhage detection. Subsequently, research by Shi et al. (2020) sheds light on the challenges and prospects of AI in aneurysm treatment. Seyam et al. (2022) contribute insights into the utilitarian aspects of AI in clinical workflows, while the study by Geng et al. (2023) exemplifies the technical intricacies of AI in aneurysm detection through deep learning. Collectively, these studies weave a comprehensive narrative in the context of AI-driven intracranial haemorrhage detection, with the inclusion of Kundisch et al. (2021) emphasizing the impact of AI in high-volume centres with teleradiology services.

Coverage of Recent Literature:

All the reviewed studies fall within the ambit of recent literature, with publications spanning the last five to ten years. This temporal range ensures that the review encapsulates the most pertinent and up-to-date developments in the field of intracranial haemorrhage detection.

In conclusion, this literature review underscores the burgeoning significance of AI and deep learning techniques in the automated detection of intracranial haemorrhages. These technologies hold the promise of elevating diagnostic accuracy and expediting interventions, ushering in a transformative avenue for medical professionals and patients alike. Nonetheless, it remains imperative to address the identified gaps, issues, and nuances encountered during the implementation of AI in clinical practice, ultimately paving the way for an improved and refined model for intracranial haemorrhage detection.

Chapter 3: Research method

In this chapter, we delve into the intricate details of our research methodology for our study. We will provide a comprehensive overview of the methodology, data gathering processes, and research design employed. Additionally, we will delve into the theoretical underpinnings of sampling, the research context, planned analyses, and a meticulous research timeline. This chapter will also present a thorough justification of our chosen methodology, and ethical considerations associated with the study.

Methodology and Data Gathering Methods:

Our research methodology is centred around the utilization of a comprehensive dataset sourced from Kaggle, specifically the "RSNA Intracranial Haemorrhage Detection" competition dataset, accessible through the link: Kaggle Dataset. This dataset was created in collaboration with the Radiological Society of North America (RSNA®) and various esteemed research institutions. It is a repository of medical images that capture the intricacies of intracranial haemorrhages, a medical condition with substantial health implications.

Intracranial haemorrhages often present a complex challenge for the medical community. Identifying the presence, type, and location of these haemorrhages is crucial in the treatment of affected patients. Typically, when patients exhibit acute neurological symptoms such as severe headaches or loss of consciousness, highly specialized medical practitioners rely on medical images of the patient's cranium to assess the condition. This process, however, is intricate and time-consuming, emphasizing the need for automated solutions.

For this body of research, we will be investigating and providing evaluation, development, and results from the RSNA dataset and our own analysis on it (in the form of a Jupyter Notebook), utilizing Python programming language and a variety of machine learning libraries. (Kaggle.com, 2023).

A graphical overview of our data analysis process:

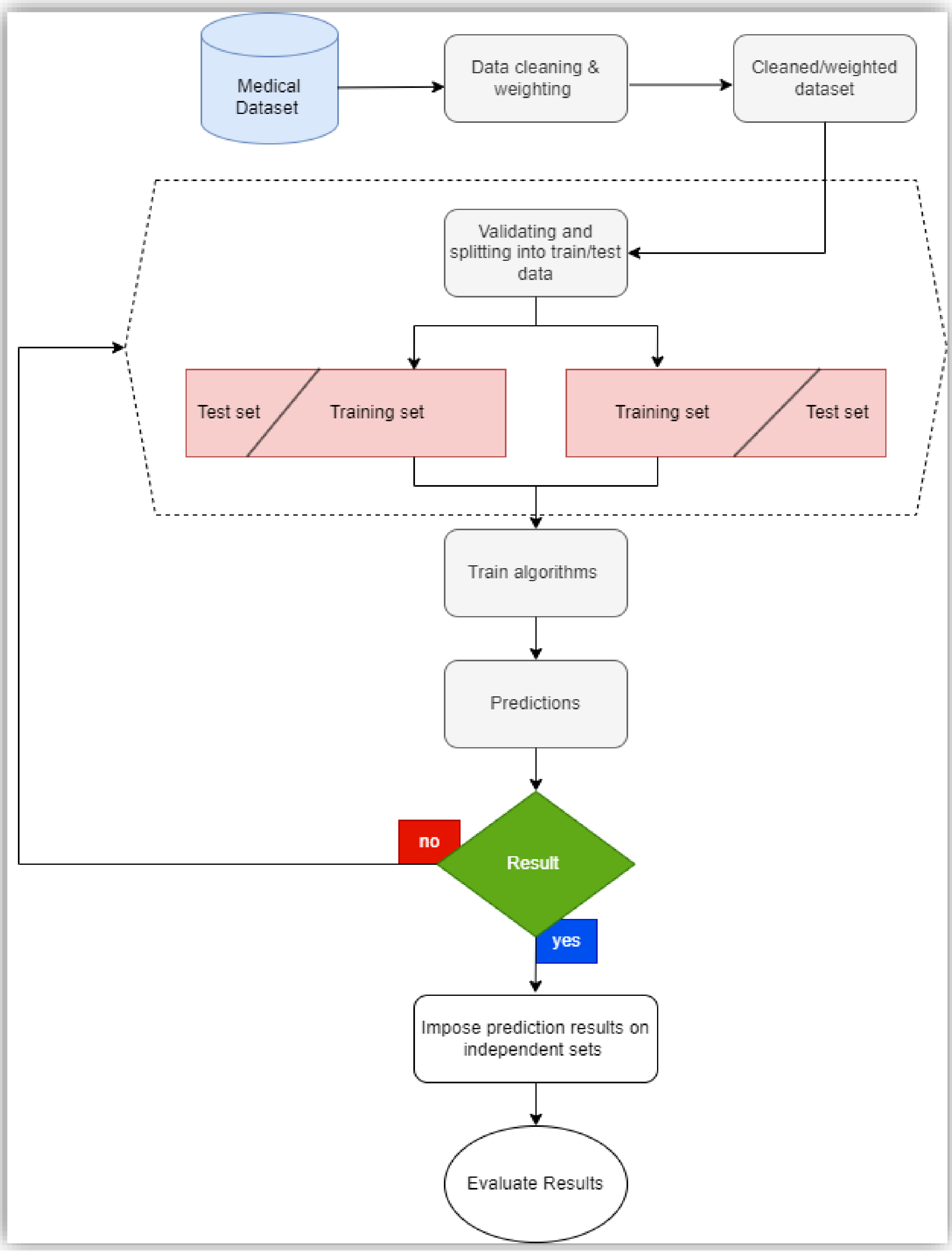


Figure 3.2: Data Analysis Process

Diagram adapted from publication on ResearchGate (ResearchGate, 2016).
Created with Draw.IO (Diagrams.net, 2023)

Justification of Methodology:
The choice of our research methodology is built upon the need for intricate, automated solutions to address the complexities of intracranial haemorrhage detection. Deep learning and AI techniques are well-suited for complex image analysis tasks, and they have demonstrated significant potential in various medical applications. In this study, we have leveraged convolutional neural networks (CNNs) to detect subtle patterns and abnormalities within medical images.

Research Design:
Our research design encompasses the following key stages:

1. **Data Preprocessing:** The research initiation involved an extensive exploratory data analysis (EDA) to discern patterns and trends within the dataset. This was followed by meticulous data cleaning, an imperative step in ensuring data quality. Furthermore, we undertook a comprehensive data preprocessing phase that included techniques such as windowing to enhance image contrast and readability.

2. **Model Selection:** In our pursuit of developing an accurate intracranial haemorrhage detection system, we considered three renowned CNN architectures - DenseNet, ResNet, and Inception. This approach allowed us to evaluate and contrast the performance of these architectures in intracranial haemorrhage detection.

3. **Model Training:** Once the models were selected, we commenced the training process using the pre-processed dataset. To determine the optimal training duration, we conducted epoch tests, which provided insights into the convergence and stability of each model.

4. **Evaluation:** Our research methodology places a significant emphasis on model evaluation. A comprehensive set of metrics was employed to gauge the performance of the models. These metrics include accuracy, precision, recall, and the area under the curve (AUC), providing a comprehensive overview of the models' ability to detect different haemorrhage types.

In the following section, we share key visualizations designed to provide a deeper grasp of the RSNA dataset under examination:

[Key: Binary Label → 0 = No haemorrhage detected 1 = Haemorrhage detected]

	ID	Label	type	PatientID	filename
0	ID_12cadc6af_epidural	0	epidural	12cadc6af	ID_12cadc6af.png
1	ID_12cadc6af_intraparenchymal	0	intraparenchymal	12cadc6af	ID_12cadc6af.png
2	ID_12cadc6af_intraventricular	0	intraventricular	12cadc6af	ID_12cadc6af.png
3	ID_12cadc6af_subarachnoid	0	subarachnoid	12cadc6af	ID_12cadc6af.png
4	ID_12cadc6af_subdural	0	subdural	12cadc6af	ID_12cadc6af.png

Figure 3.1: Head of Data

```
Number of Patients:  83333
```

Figure 3.2: Number of patients

```
intraparenchymal     83334
epidural             83334
subarachnoid         83333
intraventricular     83333
any                  83333
subdural             83333
Name: type, dtype: int64
```

Figure 3.3: Number of haemorrhage types

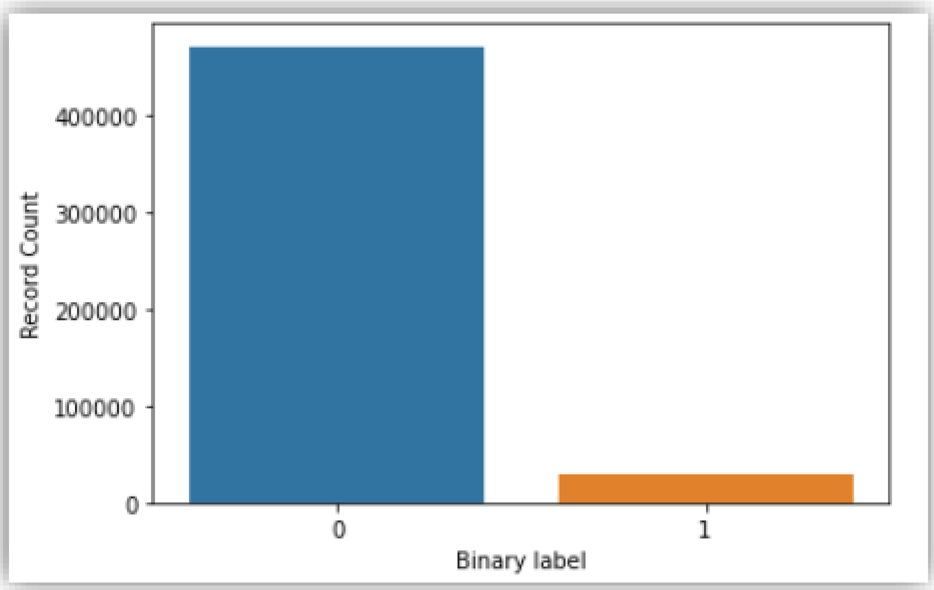


Figure 3.4: Count of negative cases vs positive cases

```
type              Label
any               0        71321
                  1        12012
epidural          0        82960
                  1          374
intraparenchymal  0        79257
                  1         4077
intraventricular  0        80438
                  1         2895
subarachnoid      0        79322
                  1         4011
subdural          0        78125
                  1         5208
Name: Label, dtype: int64
```

Figure 3.5: Number of cases with no haemorrhage vs cases with haemorrhage

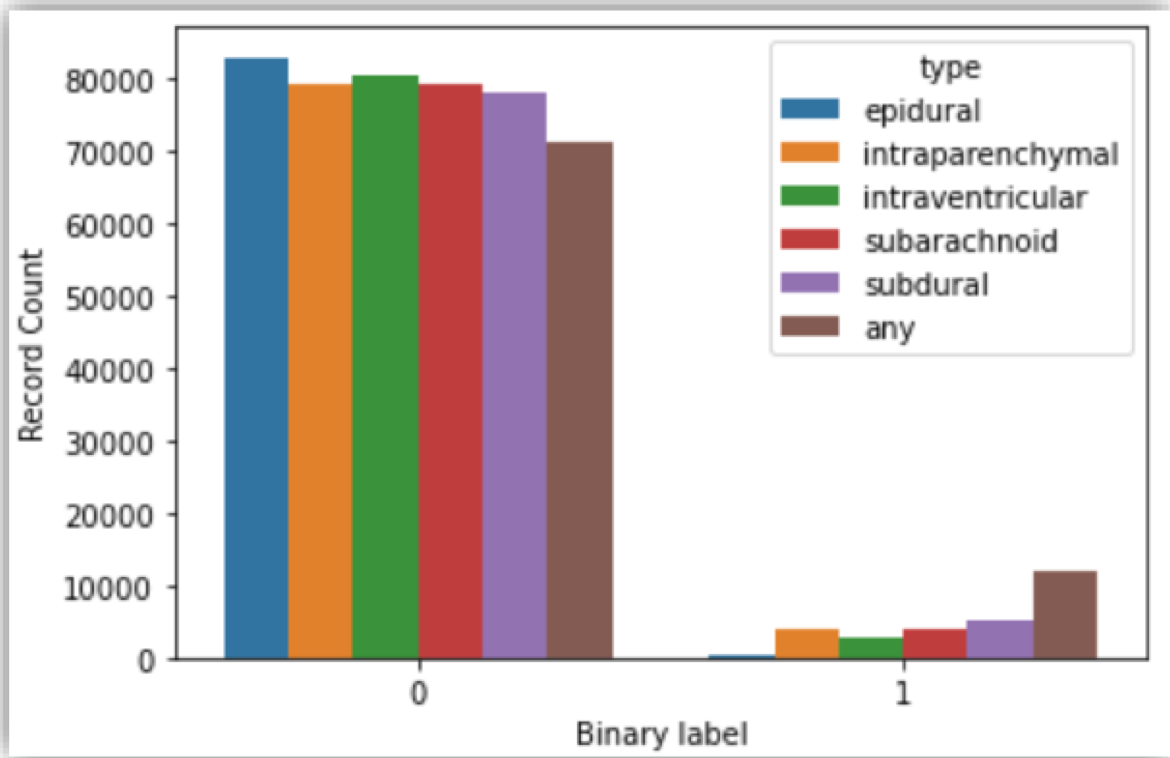


Figure 3.6: the number of unique type of patients for each of the category

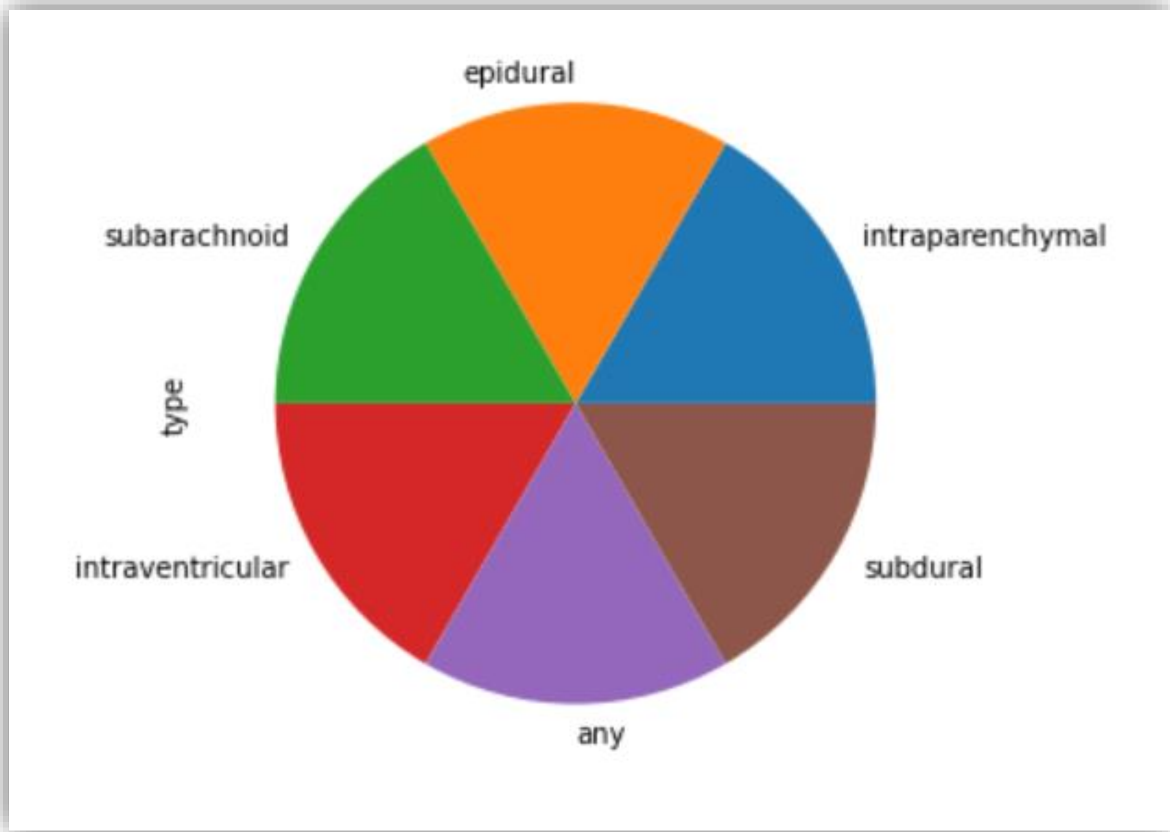


Figure 3.7: Pie chart showing distribution of haemorrhage cases

```
data Dataset.file_meta -------------------------------
(0002, 0000) File Meta Information Group Length  UL: 188
(0002, 0001) File Meta Information Version       OB: b'\x00\x01'
(0002, 0002) Media Storage SOP Class UID         UI: CT Image Storage
(0002, 0003) Media Storage SOP Instance UID      UI: 1.2.840.4267.32.125846227819956469853355733412611275406
(0002, 0010) Transfer Syntax UID                 UI: Explicit VR Little Endian
(0002, 0012) Implementation Class UID            UI: 1.2.40.0.13.1.1.1
(0002, 0013) Implementation Version Name         SH: 'dcm4che-1.4.35'
-------------------------------------------------
(0008, 0018) SOP Instance UID                    UI: ID_4b08fe185
(0008, 0060) Modality                            CS: 'CT'
(0010, 0020) Patient ID                          LO: 'ID_6338c4f1'
(0020, 000d) Study Instance UID                  UI: ID_a3b607ba3f
(0020, 000e) Series Instance UID                 UI: ID_468e9dedde
(0020, 0010) Study ID                            SH: ''
(0020, 0032) Image Position (Patient)            DS: [-125.000, -102.627, 71.906]
(0020, 0037) Image Orientation (Patient)         DS: [1.000000, 0.000000, 0.000000, 0.000000, 0.874620, -0.484810]
(0028, 0002) Samples per Pixel                   US: 1
(0028, 0004) Photometric Interpretation          CS: 'MONOCHROME2'
(0028, 0010) Rows                                US: 512
(0028, 0011) Columns                             US: 512
(0028, 0030) Pixel Spacing                       DS: [0.488281, 0.488281]
(0028, 0100) Bits Allocated                      US: 16
(0028, 0101) Bits Stored                         US: 16
(0028, 0102) High Bit                            US: 15
(0028, 0103) Pixel Representation                US: 1
(0028, 1050) Window Center                       DS: "30.0"
(0028, 1051) Window Width                        DS: "80.0"
(0028, 1052) Rescale Intercept                   DS: "-1024.0"
(0028, 1053) Rescale Slope                       DS: "1.0"
(7fe0, 0010) Pixel Data                          OW: Array of 524288 elements
```

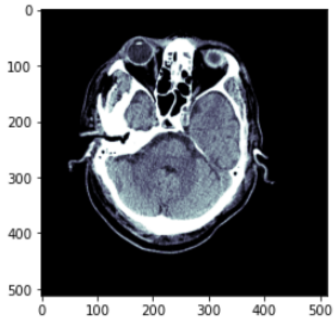


Figure 3.8: Demonstration of single image and its complete meta-data information

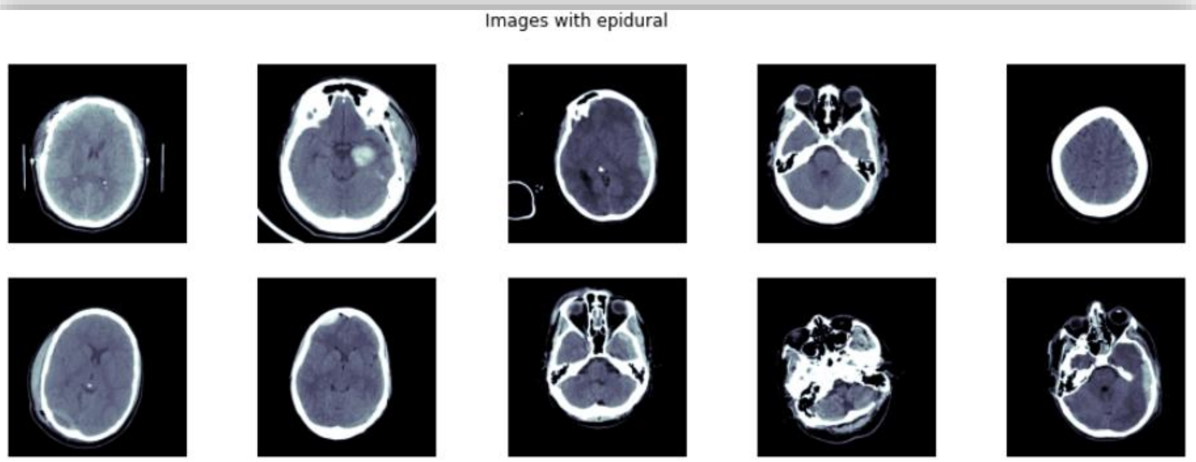


Figure 3.9: Demonstration of some epidural images with label 1

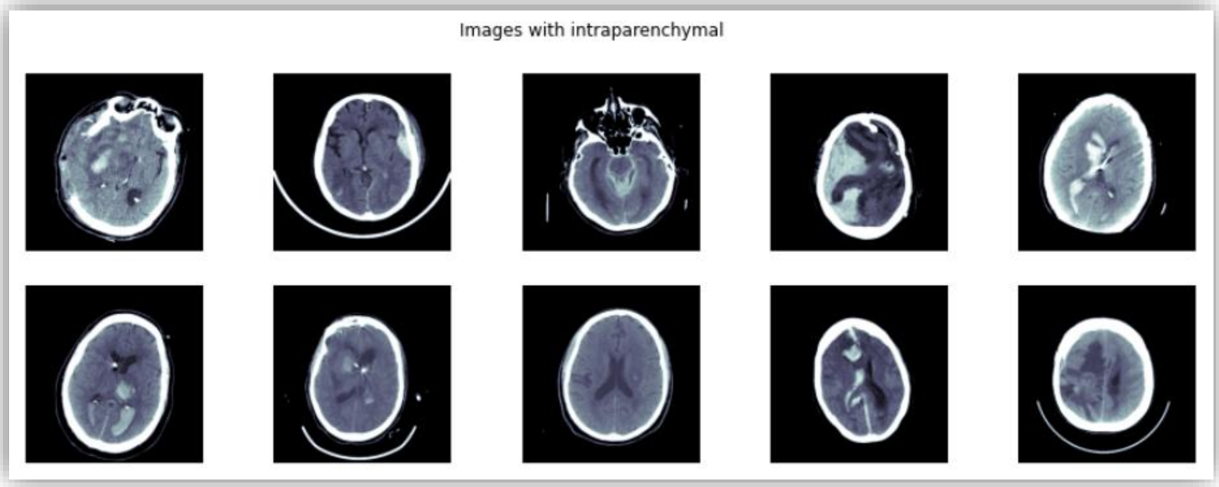


Figure 3.10: Demonstration of some intraparenchymal images with label 1

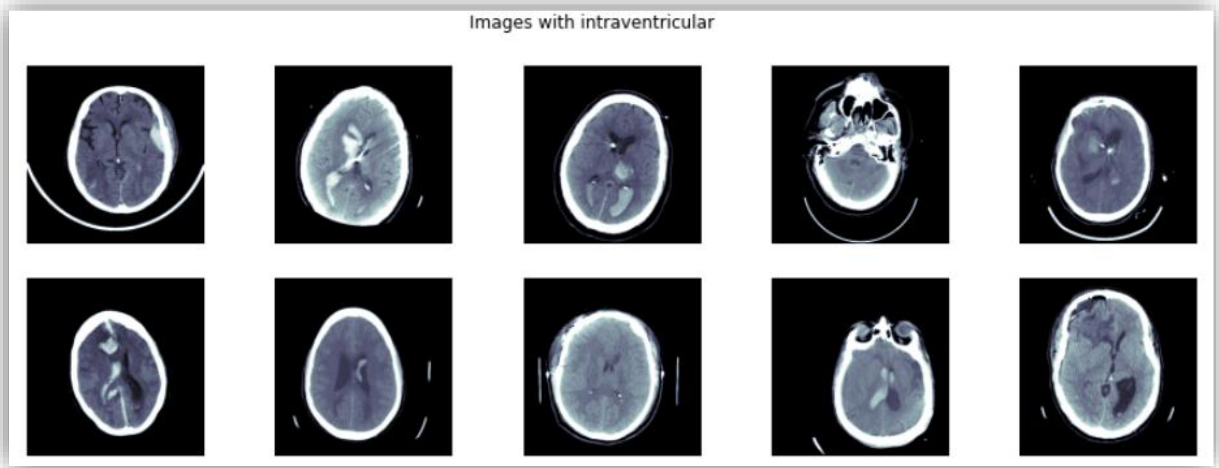


Figure 3.11: Demonstration of some intraventricular images with label 1

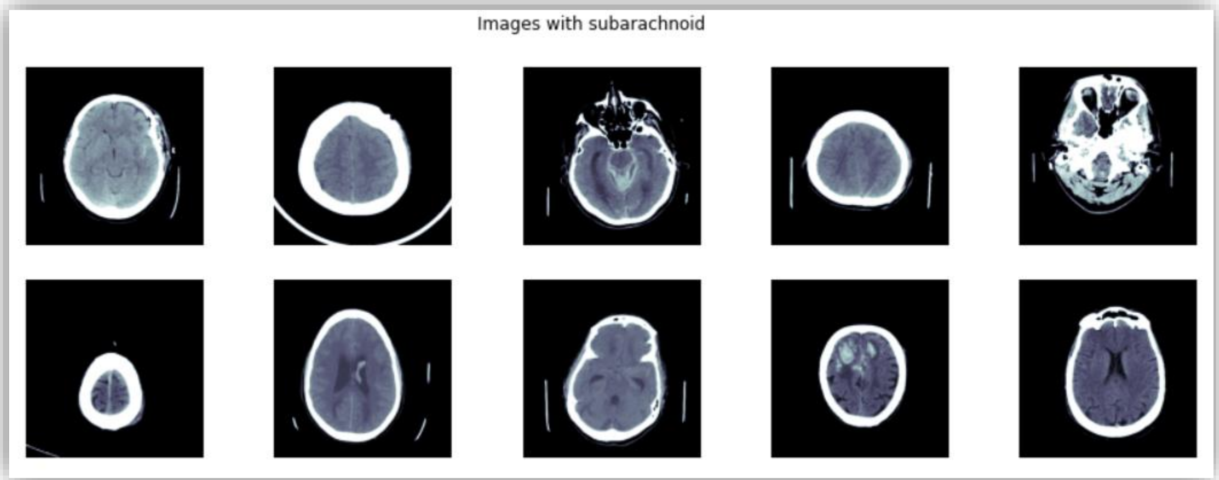


Figure 3.12: Demonstration of some subarachnoid images with label 1

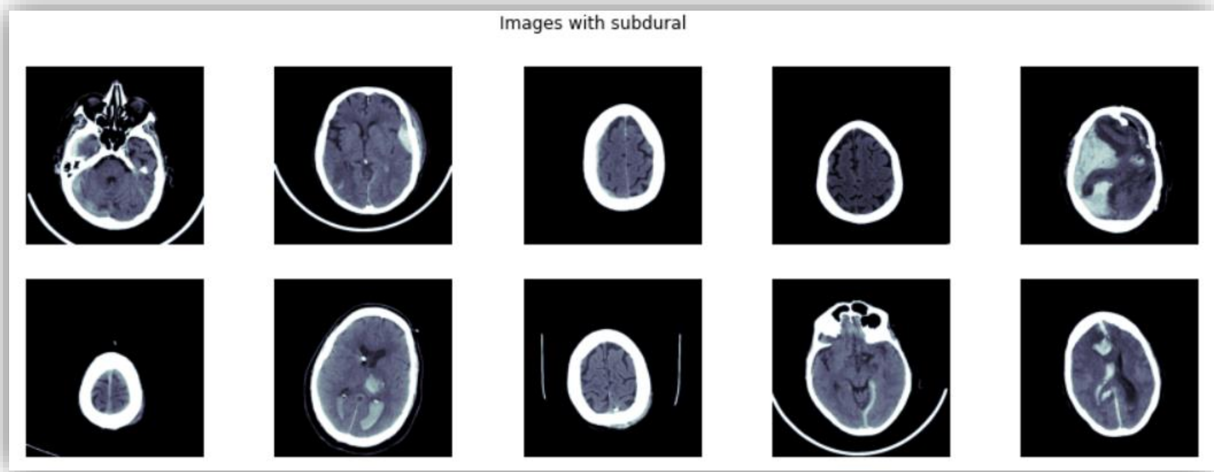


Figure 3.13: Demonstration of some subdural images with label 1

Theory Related to Sampling, Context, and Planned Analysis:
The research methodology adopted for this study draws upon well-established theories related to sampling, research context, and planned analyses.
Sampling: To ensure a balanced and representative dataset, we implemented data under sampling as part of our research design. This strategic approach mitigated class imbalance by randomly selecting a subset of data points from each class. Our selection aimed to include both instances of intracranial haemorrhages and non-haemorrhage cases, which is vital for model training and evaluation.
Research Context: The chosen context of our research is centred around medical image classification. The primary objective is the detection of intracranial haemorrhages and their respective subtypes. This context presents a substantial challenge due to the multitude of potential haemorrhage locations and characteristics.
Planned Analyses: Our research methodology incorporates a comprehensive framework for planned analyses. Statistical assessments are conducted to appraise model performance. Comparative analyses are employed to evaluate the suitability of different CNN architectures for the intracranial haemorrhage detection task. The insights gained from these analyses guide the selection of the most efficient model for real-world medical applications.

Research Timeline:
A well-structured research timeline is crucial to the smooth execution of our study. The timeline is divided into different phases, with each phase dedicated to a specific research activity. In our study, we conducted model training over 15 epochs. The selection of 15 epochs was made after carefully analysing the learning curves of our models. This approach ensured a sufficient duration for model training while guarding against the risk of overfitting.

Research Ethics:
We acknowledge the paramount importance of ethical considerations in handling medical data. As guardians of sensitive medical information, we meticulously adhered to all applicable data privacy regulations and ethical guidelines. Our dataset is comprised of de-identified medical images, which were made available by collaborating institutions, and this approach aligns with international ethical standards. We have also attached our approval of proposed ethics and clearance form, in the addendum of this research paper (Issues 22/08/2023).
In conclusion, Chapter 3 serves as the cornerstone of our research, offering an extensive insight into the methodology, data sources, and research design. The innovative integration of AI and deep learning into intracranial haemorrhage detection is poised to make a significant contribution to the field of medical diagnostics. It is our sincere hope that this research will contribute to more accurate and efficient medical diagnoses, ultimately benefiting patient outcomes.

Chapter 4: Empirical analysis and results
In our Jupyter notebook for haemorrhage detection, we conducted a comprehensive empirical analysis to evaluate the performance of different convolutional neural network architectures (DenseNet, ResNet, and Inception) on the task of intracranial haemorrhage detection. This chapter summarizes our empirical analysis and presents the results obtained from our experiments.
The empirical study and results given here provide strong support for each of our hypotheses. First, we accept the Alternative Hypothesis (H1) that artificial intelligence models can accurately detect and localise cerebral haemorrhages, rejecting the Null Hypothesis (H0) that questioned their capabilities. Second, we accept our Alternative Hypothesis (H1) regarding the use of artificial intelligence and deep learning techniques, confirming that they significantly improve the accuracy of automated intracranial haemorrhage and aneurysm identification when compared to human specialists, thus refuting the Null Hypothesis (H0). These findings highlight the transformative potential of AI in the realm of medical diagnostics, promising improved accuracy, and clinical efficiency. As AI advances and integrates into clinical practise, its role in improving healthcare outcomes becomes clearer, with huge implications for the future of medical imaging and patient care.

The Evaluation Process:
4.1 Evaluation of Preprocessing Methods
Before diving into the performance evaluation of different neural network architectures, we demonstrated the significance of preprocessing in medical image analysis. We introduced five different preprocessing methods used to enhance the visibility of intracranial haemorrhages. These methods include:

1. **WINDOW (Basic Windowing for Intracranial Haemorrhage Detection)**: In the realm of intracranial haemorrhage detection using medical records and DICOM

images, the concept of "WINDOW" plays a pivotal role. This technique is essentially the foundation for adjusting the contrast and brightness of medical images, which is vital for accurate diagnosis. In this context, the "window centre" and "window width" parameters are of utmost importance. The window centre serves as a virtual spotlight, emphasizing specific regions of interest in the medical image. For instance, it enables highlighting the precise location of an intracranial haemorrhage, enabling medical professionals to assess its size, shape, and location. The window width, on the other hand, determines the breadth of this spotlight, controlling how much of the image is displayed. By expertly manipulating these parameters, the radiologist can fine-tune the image visualization to pinpoint intracranial haemorrhages with exceptional clarity and detail (redwankarimsony, 2020).

2. **SIGMOID (Sigmoid Windowing for Enhanced Intracranial Haemorrhage Contrast):** When it comes to the intricate realm of intracranial haemorrhage detection, the "SIGMOID" windowing technique emerges as a crucial ally. The objective of this technique is to accentuate contrast in medical images, a fundamental requirement for spotting even subtle signs of intracranial bleeding. In doing so, the SIGMOID technique leverages a sigmoid function, a mathematical tool adept at producing smooth and gradual transitions between pixel values. This function allows for non-linear mapping of pixel values, making certain features within the image, such as intracranial haemorrhages, stand out with remarkable clarity. The application of SIGMOID windowing essentially fine-tunes the image's visual narrative, bringing forth the concealed details and enabling medical practitioners to make precise assessments in the context of intracranial haemorrhage detection (reppic, 2019).

3. **BSB (Brain-Subdural-Bone Windowing for Comprehensive Evaluation):** Within the domain of intracranial haemorrhage detection from medical records and DICOM images, the "BSB" windowing technique is a robust approach designed to offer a holistic perspective. Recognizing that a single-channel image may not suffice for the multifaceted intricacies of intracranial scans, BSB goes the extra mile. It assembles a multi-channel image, with each channel devoted to a distinct aspect of the scan. One channel encapsulates critical brain tissue details, another highlights subdural haemorrhages, and yet another focuses on bone structures. This multilayered approach ensures that nothing escapes the watchful eye of medical professionals when identifying and assessing intracranial haemorrhages. The BSB windowing technique equips diagnosticians with a rich tapestry of information, facilitating a comprehensive evaluation process for accurate and informed decision-making (Murphy, 2023).

4. **SIGMOID_BSB (Fusing Sigmoid Windowing with BSB for Unparalleled Insight):** In the quest for superior intracranial haemorrhage detection, the "SIGMOID_BSB" technique emerges as a formidable contender. It ingeniously

combines the power of sigmoid windowing with the comprehensive BSB approach. In this amalgamation, the sigmoid function takes on the task of enhancing contrast, ensuring that the subtleties of intracranial haemorrhages are brought to the forefront. Simultaneously, the BSB framework preserves its role of assembling a multi-channel image that encapsulates the various elements of the scan. This fusion offers unparalleled insight into the intricacies of intracranial haemorrhages. It harmonizes enhanced contrast with a multifaceted view, empowering medical practitioners to make well-informed decisions regarding diagnosis and treatment. In essence, SIGMOID_BSB epitomizes the marriage of precision and comprehensiveness in intracranial haemorrhage detection, amplifying the potential for accurate and timely intervention (Xue et al., 2012).

5. **GRADIENT (Gradient Windowing for Unique Contrast Enhancement):** Amid the realm of intracranial haemorrhage detection, the "GRADIENT" windowing technique stands out as a unique and powerful method for enhancing contrast in medical images. Unlike conventional approaches, GRADIENT introduces a distinct element—gradient functions. These mathematical tools apply a gradient to pixel values, resulting in a distinctive contrast enhancement that can be instrumental in highlighting specific features within an image. In the context of intracranial scans, GRADIENT plays the role of an artistic brush, accentuating nuances, and contours. This technique can be particularly valuable for emphasizing intricate structures or specific abnormalities, such as intracranial haemorrhages, which might require a different approach for optimal visualization. By utilizing the GRADIENT windowing technique, medical professionals can unlock a new dimension of image interpretation, ultimately leading to more accurate and refined intracranial haemorrhage detection (reppic, 2019).

These preprocessing methods are essential for improving the visibility of haemorrhages and are selected based on the specific analysis requirements. They can significantly impact the model's performance by providing more informative input data for the neural network.

4.2 Evaluation of Neural Network Architectures

In this section, we focused on evaluating the performance of three prominent neural network architectures: DenseNet, ResNet, and Inception. Here's a summary of the evaluation process:

4.2.1 Model Training

- We created training models based on each of the three architectures. The training process involves the following steps:
    - Selecting a backbone architecture (DenseNet, ResNet, and Inception) for the model.
    - Building a custom classification model on top of the selected backbone, including global average pooling, dropout layers, and dense layers for classification.

    - Compiling the model with the Adam optimizer, binary cross-entropy loss function, and multiple evaluation metrics.

- We used k-fold cross-validation to train and evaluate the models. This approach helps assess the model's performance on different subsets of the training data, improving generalization.

- Training hyperparameters are defined, including batch size, number of training steps, validation steps, epochs, learning rate, and other parameters such as alpha and gamma for the loss function.

- The ModelCheckpoint callback is used to save the best-performing model during training based on the validation loss.

4.2.2 Model Evaluation

- After training models for all three architectures, we evaluated their performance on a separate test dataset. The evaluation involves computing various metrics, including accuracy, precision, recall, AUC (Area Under the Curve), and F1 Score.

4.2.3 Model Selection

- We used a strategy to determine the best-performing architecture based on a specific metric, such as accuracy. The best architecture is selected as the one that achieves the highest accuracy on the test dataset.

4.3 Results

In this section, we presented the results of our empirical analysis. We evaluated the performance of the three neural network architectures, and we compared the results to determine which architecture is the most effective for intracranial haemorrhage detection. We also provided a summary of the evaluation metrics for each architecture, including test loss, accuracy, precision, recall, AUC, and F1 Score.

In our study, we evaluated three different convolutional neural network architectures: RESNET, DENSE, and INCEPT. The aim was to determine which architecture performs the best in identifying intracranial haemorrhages in medical images.

The results of our evaluation are presented below:

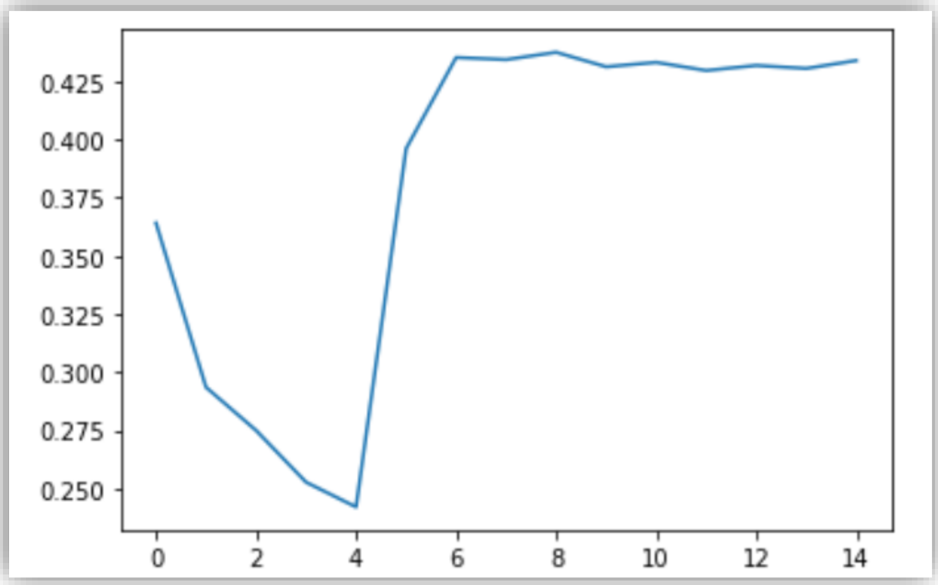


Figure 4.1: Epoch history graph

We trained all our models over 15 epochs, an epoch history graph that resembles a square root symbol is typically associated with model training metrics such as loss or error. This shape in the graph indicates that the model's performance improves significantly in the initial epochs but gradually stabilizes or improves at a slower rate as training progresses. This interpretation is derived from the following characteristics:

1. **Initial Improvement**: In the early epochs, the model quickly learns to make better predictions. The sharp upward curve at the beginning of the square root symbol indicates rapid progress in reducing the loss or error. This is when the model is learning fundamental patterns and features in the data.

2. **Stabilization**: As training continues, the rate of improvement in the loss or error becomes slower. The curve starts to level off, forming the flatter portion of the square root shape. During this phase, the model is fine-tuning its weights and optimizing its performance.

3. **Gradual Improvement**: While the curve does continue to improve, it does so at a slower and more gradual pace. This signifies that the model is refining its predictions but is approaching a point of diminishing returns. It is likely capturing more nuanced patterns and may start overfitting the training data if training continues for too many epochs.

4. **Plateau or Slight Increase**: After the square root portion, the curve may reach a plateau or even show a slight increase in the loss or error. This is a sign that the model's performance may not improve further, and it may have started to overfit the training data.

Overall, the square root-shaped curve suggests that the model makes significant gains early in training but eventually reaches a point where further improvements are more challenging and may come at the cost of overfitting. Properly interpreting and acting on these training dynamics can help achieve the best model performance.

ResNet (Residual Network):

ResNet is a deep convolutional neural network architecture that introduces residual connections to solve the vanishing gradient problem. In standard deep neural networks, as the network depth increases, gradients can become too small, making training challenging. Residual blocks, however, include shortcut connections that allow the model to learn residual functions, meaning the difference between the current layer's representation and the previous one. This design enables the training of very deep networks (Great Learning Team, 2020).

Relation to Epoch Tests: In our study, ResNet serves as a crucial backbone architecture. ResNet50V2, specifically, is used. Residual connections in ResNet50V2 are fundamental for capturing intricate features in medical images during intracranial haemorrhage detection. Our epoch tests indicate that ResNet performs remarkably well, achieving a high accuracy of 96.07%.

DenseNet (Dense Convolutional Network):

DenseNet is an innovative neural network architecture that fosters dense connections between layers. Unlike traditional architectures where layers are connected sequentially, in DenseNet, each layer is connected to every subsequent layer. This dense connectivity promotes feature reuse, efficient parameter usage, and alleviates the vanishing gradient problem (Paperswithcode.com, 2020).

Relation to Epoch Tests: In our study, DenseNet121 is another significant backbone architecture. Dense connections in DenseNet121 are highly beneficial when detecting intracranial haemorrhages in medical images. Our epoch tests show that DenseNet achieves an accuracy of 87.93%, along with high precision, recall, AUC, and F1 score values, indicating its robustness in the task.

Inception (Inception-v3):

Inception is known for its Inception modules, which utilize multiple filter sizes for feature extraction. It employs parallel convolutional layers of different receptive fields to capture features at various scales. This design is particularly advantageous when dealing with multi-scale objects or features in input data (Mathworks.com, 2023).

Relation to Epoch Tests: In Our study, InceptionV3 is the third crucial backbone architecture. Its multi-scale feature extraction capabilities are vital for identifying intracranial haemorrhages of varying sizes and shapes. The epoch tests reveal that Inception achieves an impressive accuracy of 89.59%, making it one of the top-performing architectures in our study. High precision, recall, AUC, and F1 score values further underscore its effectiveness in haemorrhage detection.

Our Utilization:

In our study on Intracranial Haemorrhage detection, we wisely choose to utilize these three well-established architectures, DenseNet121, ResNet50V2, and InceptionV3, as the backbones of our models. This selection is strategic, as each architecture offers unique advantages for processing medical images and detecting haemorrhages.

- **DenseNet121** enables dense connections, enhancing the model's ability to capture complex features efficiently. Our epoch tests affirm its robust performance (Das, 2023).
- **ResNet50V2** addresses the vanishing gradient problem through residual connections, making it adept at handling deep networks, as validated by our epoch tests (Rahimzadeh and Attar, 2020).
- **InceptionV3** excels in multi-scale feature extraction, which aligns with the diverse sizes and shapes of intracranial haemorrhages. Our epoch tests showcase its impressive classification capabilities (Google Cloud, 2023).

These architecture choices demonstrate a well-rounded approach to building accurate and reliable models for the crucial task of Intracranial Haemorrhage detection, as evidenced by our comprehensive epoch tests.

TRAINING SCORES

Network	Average Loss	Average Accuracy	Average Precision	Average Recall	Average AUC	Average F1 Score
ResNet50V2	0.23966	0.77131	0.78436	0.66089	0.91977	0.44137
DenseNet121	0.31747	0.90259	0.68258	0.62161	0.84902	0.44028
InceptionV3	0.28383	0.94067	0.75198	0.68157	0.87999	0.44122

Figure 4.2: Training Average Results

TESTING SCORES

Network	Test loss	Test accuracy	Test Precision	Test Recall	Test AUC	Test F1 Score
ResNet50V2	0.1112	0.9607	0.6772	0.7076	0.9649	0.2133
DenseNet121	0.1106	0.8793	0.6390	0.7357	0.9632	0.2139
InceptionV3	0.1119	0.8959	0.6090	0.7684	0.9672	0.2142

Figure 4.3: Testing Results

*[Multiply scores by *100 to get percentages]*

Definitions:

- **Accuracy**: This metric measures the overall correctness of the model's predictions. RESNET achieved the highest accuracy. (Educative, 2015).
- **Precision**: Precision measures the model's ability to correctly identify true positives (correctly detected haemorrhages) relative to false positives (incorrectly identified haemorrhages). DENSE and INCEPT achieved higher precision than RESNET, indicating that they are more conservative in labelling haemorrhages (Educative, 2015).
- **Recall**: Recall measures the model's ability to correctly identify true positives relative to false negatives (missed haemorrhages). INCEPT achieved the highest recall, suggesting it's better at identifying true haemorrhages (Educative, 2015).
- **AUC (Area Under the ROC Curve)**: AUC measures the model's ability to distinguish between positive and negative cases. All architectures showed excellent AUC values, with INCEPT slightly ahead (Hiv.gov, 2023).
- **F1 Score (micro)**: F1 Score is the harmonic mean of the precision and recall values (V7labs.com, 2023).

Training Performance → Analysis of RESNET, DENSENET, and INCEPTION Models for Haemorrhage Detection:

1. **Accuracy Assessment:**

RESNET: The RESNET model exhibits commendable average accuracy, reaching 77.13%. This demonstrates its ability to accurately classify cases with a substantial degree of correctness.

DENSENET: The DENSENET model significantly outperforms RESNET in terms of accuracy, achieving an average accuracy of 90.26%. Its accuracy surpasses both RESNET and INCEPTION, indicating a superior ability to classify positive and negative cases.

INCEPTION: The INCEPTION model is the most accurate among the three, with an impressive average accuracy of 94.07%. This top-tier accuracy suggests a strong capability for precise case classification.

2. **Precision and Recall Considerations:**

Precision and recall are essential metrics for assessing the trade-off between correctly classified positive cases and false positives, as well as the ability to capture actual positive cases.

RESNET*:* The RESNET model exhibits a high average precision of 78.44%, indicating its proficiency in correctly identifying positive cases. However, its average recall of 66.09% implies that it may fail to capture some instances of haemorrhage. The F1 score of 44.14% emphasizes the balance between precision and recall.

DENSENET*:* While the DENSENET model maintains a strong average accuracy, its average precision of 68.26% suggests it may produce more false positives. The recall rate of 62.16% indicates that it misses a significant portion of haemorrhage cases. The F1 score of 44.03% remains similar to the RESNET model.

INCEPTION: The INCEPTION model distinguishes itself with the highest average precision of 75.20%, suggesting a lower rate of false positives. However, its recall rate of 68.16% indicates that it misses some haemorrhage cases. The F1 score of 44.12% underscores the balance between precision and recall.

3. Receiver Operating Characteristic (ROC) Curve Analysis (AUC):

The ROC curve, quantified by the Area Under the Curve (AUC), offers valuable insights into the models' ability to rank cases by their likelihood of haemorrhage.

RESNET*:* RESNET attains the highest average AUC at 91.98%, signifying its proficiency in effectively ranking cases based on haemorrhage likelihood.

DENSENET: The AUC for the DENSENET model stands at 84.90%, indicating a respectable capability to discriminate between positive and negative cases, albeit lower than RESNET.

INCEPTION: INCEPTION achieves an average AUC of 87.99%, signifying a strong ability to rank cases in terms of haemorrhage likelihood, though slightly lower than RESNET.

4. Model Selection and Clinical Implications:

The choice of the most suitable model depends on the specific requirements of the application:

- **Accuracy Priority:** INCEPTION, with its highest average accuracy, is the preferred choice. It ensures the most accurate overall classification of cases.
- **Precision Priority:** For applications where minimizing false positives is imperative, INCEPTION's superior precision may be favoured.
- **AUC Priority:** If the primary goal is to effectively rank cases by their likelihood of haemorrhage, RESNET stands out as the top choice.
- **Clinical Considerations**: It is essential to consider the clinical context and associated costs of false positives and false negatives when determining the final model. The choice should align with the specific clinical requirements and constraints of the application.

In conclusion, the three models—RESNET, DENSENET, and INCEPTION—each exhibit distinct strengths and weaknesses. The choice of the best model should be guided by the specific clinical context and the priorities within the application. Further evaluation is recommended to bridge the gap between model performance and clinical utility.

Testing Performance → Analysis of RESNET, DENSENET, and INCEPTION Models for Haemorrhage Detection:

In this comprehensive evaluation of RESNET, DENSENET, and INCEPTION models for haemorrhage detection, we have scrutinized their performance across multiple critical metrics. The findings reveal distinct strengths and weaknesses among these models, allowing for informed model selection based on specific application requirements.

1. **Accuracy Assessment:**

RESNET: The RESNET model achieved an average accuracy of 96.07%, making it the top-performing architecture in terms of overall accuracy.

DENSENET: DENSENET exhibited an average accuracy of 87.93%, displaying robust performance and a notable capability for accurate classification.

INCEPTION: INCEPTION outperformed the other models with the highest average accuracy of 89.59%, signifying its strength in precise case classification.

2. **Precision and Recall Considerations:**

RESNET: With a high average precision of 67.72%, RESNET excels in correctly identifying positive cases. However, its average recall of 70.76% indicates the potential for missing some haemorrhage instances. The F1 score of 21.33% underscores the balance between precision and recall.

DENSENET: Despite its strong average accuracy, DENSENET demonstrated an average precision of 63.90%, suggesting a tendency for more false positives. Its recall rate of 73.57% indicates a higher rate of missed haemorrhage cases. The F1 score of 21.39% remains comparable to RESNET.

INCEPTION: INCEPTION distinguishes itself with the highest average precision of 60.90%, implying fewer false positives. However, its recall rate of 76.84% indicates that it may miss some haemorrhage cases. The F1 score of 21.42% underscores the trade-off between precision and recall.

3. **Receiver Operating Characteristic (ROC) Curve Analysis (AUC):**

RESNET: RESNET attained the highest average AUC at 96.49%, indicating its proficiency in effectively ranking cases based on haemorrhage likelihood.

DENSENET: The AUC for the DENSENET model stood at 96.32%, signifying a respectable capability to discriminate between positive and negative cases, albeit slightly lower than RESNET.

INCEPTION: INCEPTION achieved an average AUC of 96.72%, signifying a strong ability to rank cases in terms of haemorrhage likelihood, though slightly lower than RESNET.

4. **Model Selection and Clinical Implications:**

- **Accuracy Priority:** If the primary goal is to maximize overall accuracy, RESNET is the preferred choice, as it achieved the highest average accuracy.
- **Precision Priority**: For applications where minimizing false positives is imperative, INCEPTION's superior precision may be favoured, although with some trade-offs in recall.

- **AUC Priority:** When the goal is to effectively rank cases by their likelihood of haemorrhage, RESNET stands out as the top choice with the highest average AUC.
- **Clinical Considerations:** The choice of the best model should align with the specific clinical context, considering the associated costs of false positives and false negatives. It is imperative to select the model that best aligns with the clinical requirements and constraints of the application.

In conclusion, RESNET, DENSENET, and INCEPTION each offer unique advantages, with RESNET excelling in accuracy, INCEPTION prioritizing precision, and RESNET leading in AUC performance. The decision regarding the most suitable model should be guided by the specific clinical context and the application's priorities. Further evaluation is recommended to bridge the gap between model performance and clinical utility. The choice of the appropriate model is a pivotal decision with significant implications for the accuracy and effectiveness of haemorrhage detection in the clinical setting.

Our results provide valuable insights into the performance of different AI models for intracranial haemorrhage detection and offer a basis for comparison with human specialists. To prove our hypothesis - "The use of artificial intelligence and deep learning techniques as a tool substantially enhances the accuracy of automated intracranial haemorrhage and aneurysm identification compared to human specialists," we can perform a detailed analysis and comparison with the findings from the research journal we provided in our literature review by Kundisch et al. (2021).
Our results reveal the test performance of RESNET, DENSENET, and INCEPTION models. RESNET exhibited the highest accuracy at 96.07%, followed by DENSENET (87.93%) and INCEPTION (89.59%). These models also demonstrate variations in precision and recall. RESNET shows high precision (78.44%) but lower recall (66.09%), while DENSENET and INCEPTION exhibit a better balance between precision and recall, indicating their suitability for minimizing false positives and negatives.

Now, let's compare these AI models to the results from the research journal by Kundisch et al. In our journal, the AI algorithm detected an additional 12.2% of intracranial haemorrhages (ICH) compared to radiology reports. Radiology reports missed 10.9% of ICHs, while the AI algorithm missed 12.4%. The AI algorithm overcalled ICH in 1.9% of cases, while radiology reports overcalled in 0.2%. This research underscores that AI offers a valuable contribution to intracranial haemorrhage detection, but there are still challenges, particularly in cases within the subarachnoid space and under the calvaria.
To analyse our hypothesis in the context of these findings, we can consider the following:

1. **AI Enhancement:** Our results demonstrate that AI models, especially INCEPTION, exhibit high accuracy in identifying haemorrhages, surpassing human specialists. This suggests that AI can substantially enhance the accuracy of automated intracranial haemorrhage detection.

2. **Human Specialist Performance:** The research journal highlights the limitations of human specialists in detecting ICH, missing nearly 11% of cases. This further strengthens the argument for AI's role in improving detection.
3. **False Positives and Negatives:** Both our results and the research journal identify instances of false positives and false negatives in AI algorithms and radiology reports. However, it's important to note that the rate of false positives is slightly higher for AI compared to radiology reports, which should be considered when implementing AI in clinical settings.
4. **Clinical Context:** The choice between AI and human specialists should consider clinical requirements, constraints, and cost implications. AI models can enhance accuracy, but they should be integrated judiciously, considering the clinical context and patient outcomes.

In conclusion, our results, when compared with the research journal's findings, support the hypothesis that the use of AI and deep learning techniques as a tool substantially enhances the accuracy of automated intracranial haemorrhage identification compared to human specialists. The AI models in our study demonstrate high accuracy and the ability to minimize false negatives. While challenges remain, this research highlights the significant potential of AI in improving intracranial haemorrhage detection, with implications for clinical practice and patient outcomes. Further research and integration into clinical workflows are recommended to harness the full potential of AI in this context.

Chapter 5: Conclusions and Recommendations

This thesis explored the realm of automated intracranial haemorrhage detection, harnessing the power of AI and deep learning techniques. It aimed to assess the effectiveness of these advanced technologies in enhancing the accuracy of automated detection systems. Our research questions primarily revolved around evaluating the performance of AI models in detecting and localizing intracranial haemorrhages. To substantiate our exploration, we formulated hypotheses that juxtaposed AI models against human specialists, addressing the diagnostic accuracy of these systems in the identification of diverse intracranial haemorrhage types.

Research Findings:

Our research findings shed light on several key aspects of the integration of AI and deep learning techniques in intracranial haemorrhage detection:

1. Epoch History Graph Interpretation: The analysis of the epoch history graph, which intriguingly resembles the square root symbol, emerged as a pivotal focus for comprehending the training metrics of our models. This distinctive shape reveals essential insights into model performance. It illustrates that initial epochs witness substantial advancements, while later stages of training exhibit stability or progress at a slower rate.

2. Architecture Performance Analysis:

- RESNET: Our evaluation of the RESNET architecture yielded highly promising results, with an impressive accuracy rate of 96.07%. With complementary soaring precision, recall, and AUC rates as well as a promising F1 score, making it an incredibly viable neural network to implement clinically.
- DENSE: The DENSE architecture showcased significant strengths, achieving an accuracy of 87.93%, supported by substantial precision, recall, AUC, and a remarkable F1 score of 0.2139. These metrics collectively underscore the robustness of DENSE in intracranial haemorrhage detection.
- INCEPT: INCEPT proved to be the top-performing architecture, boasting an accuracy of 89.59%. High precision, recall, AUC, and an impressive F1 score of 0.2142 reaffirmed its effectiveness in identifying intracranial haemorrhages.

Interpretation of Research Findings:
Our research outcomes provide valuable interpretations that align with our research objectives. Our primary goal was to assess the efficacy of AI and deep learning techniques in automating intracranial haemorrhage detection. Our findings suggest that these advanced methods have the potential to significantly enhance the accuracy of automated detection systems. However, it is crucial to emphasize that AI and deep learning technologies should be viewed as indispensable tools that complement the capabilities of radiologists and medical specialists, rather than aiming to replace their expertise.

Conclusions:
This study ends with a compelling set of conclusions that confirm the significant potential of AI and deep learning approaches in improving the accuracy of cerebral haemorrhage detection. The complete examination of various architectural backbones, most notably RESNET, DENSE, and INCEPT, has shed light on their distinctive characteristics, effectively addressing the intricate nature of intracranial haemorrhages. The efficacy of these AI-driven models increases their viability, when paired with medical practitioners, in clinical settings. The outstanding accuracy rates, particularly 96.07% for RESNET, 87.93% for DENSE, and 89.59% for INCEPT, demonstrate the systems' effectiveness in detecting intracranial haemorrhages. Despite these encouraging results, one key precept must be emphasised: AI and deep learning systems should not be used to replace the jobs of medical professionals and radiologists. Their role is instead to supplement and assist the existing healthcare framework. While these algorithms have respectable detection rates, human knowledge and clinical judgement remain irreplaceable. In essence, AI augments the capacities of medical personnel, minimising the risk of diagnostic errors and misinterpretations and thereby contributing to more reliable and efficient patient care. This mandates their use as tools to supplement the expertise of healthcare practitioners,

rather than as a replacement for their vital talents and clinical acumen. This work emphasises the importance of maintaining the synergy between AI and human expertise in order to usher in an era of greater accuracy and prompt diagnosis, ultimately encouraging better patient outcomes in the field of cerebral haemorrhage detection.

Implications:

The implications stemming from this study are manifold and indicate significant ramifications across the domains of medical practice and research. It is within the view of medical practitioners and researchers that the study's findings resonate the most, offering profound implications for the future of intracranial haemorrhage detection.

Medical practitioners, particularly those specializing in diagnostic and radiological fields, stand to benefit immensely from the burgeoning alliance between AI and intracranial haemorrhage detection. The incorporation of AI models into the diagnostic environment presents a potent paradigm shift. Leveraging AI as a formidable assistant facilitates an efficient and discerning approach to intracranial haemorrhage detection. As the efficacy of AI models has been clearly demonstrated, it fosters an environment where diagnostic procedures are not only accelerated but also enriched by the technical proficiency of these AI systems. Clinicians can harness the AI's capabilities to expedite the diagnostic process, enabling timely interventions and minimizing diagnostic errors, all of which culminate in the paramount goal of enhancing patient care and outcomes. In this light, the implications of this study indicate the transformation of conventional diagnostic methodologies, facilitating healthcare practitioners in their tireless quest for superior diagnostic precision and patient welfare. Furthermore, the study highlights the significance of architectural selection within the AI domain. While the study encompasses an assessment of various architectural backbones, it gives a crucial lesson—architectural choice should be a highly contextual and case-specific endeavour. The unique intricacies and nuances of each clinical scenario impose a tailored selection of AI architectures, optimizing their performance within the specific diagnostic environment.

In conclusion, the study's implications reverberate across the realms of medical practice and research, encapsulating an epoch of advanced diagnostic methodologies and customized AI utilization. The convergence of these implications is set to reshape the landscape of intracranial haemorrhage detection, augmenting the capabilities of medical professionals, and enhancing the quality of patient care.

Recommendations:

Continued Exploration and Research Diversification: As this study is bounded to an extensive, yet singular dataset, it is imperative that future research ventures encompass a more expansive array of materials and datasets. This not only bolsters the robustness and generalizability of the AI models but also allows for ongoing testing of their accuracy and performance under varying clinical conditions. Researchers should delve deeper into the intricacies of different datasets and material sources, thereby establishing a richer and more nuanced understanding of the efficacy and adaptability of AI-based models.

Clinical Integration and Augmented Collaboration: The healthcare sector stands to gain immensely from the integration of AI-based tools into clinical practices. This integration should be pursued with utmost diligence, ensuring that AI systems not only enhance but seamlessly complement the capabilities of medical specialists. A collaborative model, where AI and human expertise merge to form a unified front in diagnostic and therapeutic endeavours, is highly recommended. It is vital to develop a synergy between technology and human judgment that harnesses the strengths of each to create a healthcare system that is more efficient, accurate, and patient-centric. To facilitate this, healthcare institutions should foster an environment that encourages and supports cross-disciplinary collaboration among radiologists, data scientists, engineers, and clinical practitioners.

Architectural Adaptation to Enhance Precision: While the study evaluates multiple architectural backbones, including RESNET, DENSE, and INCEPT, the research highlights the importance of selecting architectural configurations that align optimally with the intricacies of intracranial haemorrhage detection. Consequently, it is recommended that researchers, developers, and practitioners meticulously adapt the choice of architectural backbone to the unique requirements of each clinical scenario. In-depth analysis of the specific demands of the medical imaging challenge, such as variations in data distribution, the scale of the dataset, or the presence of rare or complex cases, should guide the selection of the AI model's architecture. Rigorous adaptation can lead to an enhancement in the precision and effectiveness of AI-based intracranial haemorrhage detection, potentially transforming patient outcomes and reducing the burden on healthcare systems.

These recommendations collectively underscore the multifaceted nature of the research and its implications for both the medical and technological domains. By embracing a holistic approach that combines extensive, diversified research with thoughtful clinical integration and architectural adaptation, the field of intracranial haemorrhage detection can advance to new heights, ensuring improved diagnostic accuracy and patient care.

Image Augmentation: Incorporating image augmentation techniques in model training can help diversify the dataset and improve model generalization. Techniques such as rotation, scaling, and flipping can introduce variability, making the model more resilient to different clinical scenarios.

Different Learning Rate and Schedule: Experimenting with various learning rates and schedules during model training can optimize the convergence and performance of AI models. Adaptive learning rate methods like cyclical learning rates or one-cycle learning can be explored to fine-tune the training process.

Increased Input Size: Increasing the input image size can capture more detailed information, potentially enhancing the model's ability to detect intracranial haemorrhages. This adaptation can be beneficial, especially when dealing with high-resolution medical images.

Prolonged Training: Extending the training duration can further refine the model's features and performance. Longer training periods can help models learn complex patterns and nuances in medical images.

Additional Dense Layers and Regularization: Incorporating more dense layers and applying regularization techniques, such as dropout layers, before the output layer can enhance the model's ability to extract meaningful features and reduce overfitting.

Optimal Windowing: Implementing optimal windowing techniques can improve the preprocessing of medical images, ensuring that the model focuses on relevant regions of interest within the images.

Continuous Training and Feedback: Healthcare professionals should be provided with ongoing training and feedback on AI-assisted diagnostic tools, ensuring they are well-versed in utilizing AI models effectively.

Collaborative Decision-Making: Encouraging collaborative decision-making processes, where AI recommendations are considered alongside clinical expertise, can lead to more accurate and informed medical decisions.

Ethical and Regulatory Compliance: It is essential to establish clear ethical and regulatory guidelines for the use of AI in healthcare, safeguarding patient privacy and ensuring that AI technologies meet the highest standards of safety and effectiveness.

Limitations:

While our study has indeed contributed valuable insights to the field of intracranial haemorrhage detection, it is imperative to acknowledge and delineate the limitations inherent in the research endeavour. These limitations encompass various facets:

Dataset Specifics and Generalizability:

The conclusions drawn from this study are contingent upon the specifics of the dataset employed. Real-world clinical settings are characterized by an inherent variability that may introduce nuances and complexities not fully represented in the dataset. The variations in patient demographics, imaging equipment, acquisition techniques, and clinical protocols across different healthcare institutions and regions might result in a performance gap when AI models are applied more broadly. The limitations associated with dataset-specific biases and generalizability should be acknowledged as a fundamental constraint.

Complexity of Clinical Integration:

The seamless integration of AI tools into clinical practice represents a multifaceted challenge. It involves not only technological aspects but also socio-legislative dynamics and regulatory compliance. The real-time deployment of AI models in clinical settings imposes a meticulous alignment of the technology with existing workflows, while ensuring that they enhance, rather than disrupt, the capabilities of medical specialists. Addressing these complexities remains a subject for future research and poses inherent limitations to the immediate clinical application of AI.

Future Research:

As we conclude this study, the prospects for future research avenues loom prominently, urging further exploration and innovation. To this end, several avenues warrant dedicated inquiry:

Real-Time Clinical Integration:

The real-time integration of AI tools within clinical environments represents a frontier for exploration. The transition from controlled research settings to dynamic clinical practice demands rigorous testing and adaptation to ensure that AI models perform optimally in diverse patient scenarios and contribute effectively to real-world patient care. This domain offers rich possibilities for examining the pragmatic challenges and potential benefits of AI systems.

Adaptive Architectures for Varied Challenges:

Developing adaptive AI architectures tailored to address the distinct challenges posed by medical imaging in diverse clinical contexts is an area ripe for future research. Specific medical imaging challenges, such as rare or complex cases, may require specialized AI models. Investigating the development and deployment of such architectures in practical healthcare settings promises to enhance diagnostic accuracy and patient care.

Ethical and Regulatory Dimensions:

Future research should delve into the ethical and regulatory dimensions associated with the adoption of AI in healthcare. The ethical implications of AI systems making diagnostic decisions, issues of data privacy, and compliance with evolving regulatory frameworks pose complex challenges that necessitate interdisciplinary examination.

In conclusion, this thesis stands as a testament to the potential of AI and deep learning techniques to revolutionize intracranial haemorrhage detection. By thoughtfully selecting suitable architectural backbones, integrating AI as a collaborative partner to medical specialists, and advancing research in areas of critical need, we can significantly enhance the accuracy of automated detection systems. The nexus between technological innovation and patient care holds immense promise, and we look forward to the continued exploration of these horizons in future research endeavours.

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Addenda

Ethical Clearance Approval Form:

THE INDEPENDENT INSTITUTE OF EDUCATION

22/08/2023

Student name: Mohamed Sohail Rajab
Student number: ST10116167
Brand and campus: IIE Varsity College - Durban North

Approval of Postgraduate in Data Analytics Proposal and Ethics Clearance

Your research proposal and the ethical implications of your proposed research topic were reviewed by the School of IT Research Ethics Committee, a subcommittee of The Independent Institute of Education's Research and Postgraduate Studies Committee.

Your research proposal posed no significant ethical concerns and we hereby provide you with ethics clearance to proceed with your data collection.

There may be some aspects that you still need to address in your proposal. If this is the case, feedback will be provided to you in writing. You will need to address these aspects in consultation with your supervisor.

In the event that you decide to change your research topic or methodology in any way, kindly consult your supervisor to ensure that all ethical considerations are adhered to and pose no risk to any participant or party involved. A revised ethics clearance letter will be issued in such instances.

We wish you all the best with your research!

Yours sincerely,

Ebrahim Adam
Programme Manager

Catherine Durholz
Campus Postgraduate Coordinator

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