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An Improved Deep Learning Framework for the Adoption of Metaverse in Medical Image Processing

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Abstract: Interest is surging among technology companies and industries with respect to the idea of what has come to be called the "metaverse": A "virtual" (or digital) world where humans may interact with one another in real-time, as well as participate in activities. Many have begun to explore how the concept may affect the future development of many areas. For instance, the medical imaging industry has also begun to examine how to leverage the potential benefits of the Metaverse, where individuals may experience what it might be like to see and interpret a medical image. The adoption of medical imaging in the Metaverse could still benefit greatly from greater standardization and the development of workflows for integrating deep learning (DL) into this new environment. The authors develop an improved DL framework by combining established DL strategies with VR technologies, thereby improving both efficiency and accuracy for processing medical images. They specifically highlight how incorporating VR headsets into medical image processing enables presentation of medical image data via a 3D virtual environment. The technology engages healthcare providers and uses 3D medical imaging data to improve data analysis. The model had 97.11% accuracy, 98.32% precision, 98.66% recall, and 95.60% F1-score. Pre-existing deep learning networks can be quickly adapted for virtual world applications using transfer learning and modular neural networks. This will reduce the time and cost of creating metaverse-specific models.

Keywords: Medical Professionals; Virtual Environment; Rapid Adaptation; Neural Networks; Healthcare Technology; Comprehensive Solution; Model Accuracy; Data Analysis; Digital Health.

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1. Introduction

The Metaverse, or the shared virtual space, is attracting serious interest from many parties for its possible impact on how researchers communicate and engage with one another in a virtual reality (VR) environment [1]. The Metaverse's influence on

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medical imaging could revolutionize healthcare delivery and improve patient care [2]. The ability to construct virtual reality is one of the main applications of the Metaverse in medical imaging, such as patient avatars [3]. A virtual avatar represents a living person in a virtual world, which can be manipulated and interacted with in that space [4]. This provides healthcare providers with an immersive, engaging view of the patient record and associated images, enabling them to review the records and assess the patient's status [5]. In addition, virtual avatars provide a richer experience for healthcare workers by enabling them to visualize the patient, connect with them, learn more about their condition, and develop treatment plans [6]. These examples of how the Metaverse can be used are illustrated in Figure 1. The use of the Metaverse enables healthcare professionals to collaborate and communicate [7]. Access to patient information in real time enables healthcare professionals in different areas to come together electronically to evaluate and discuss medical imaging, improving information sharing and decision-making, and creating more precise diagnoses and treatment plans for patients [8].

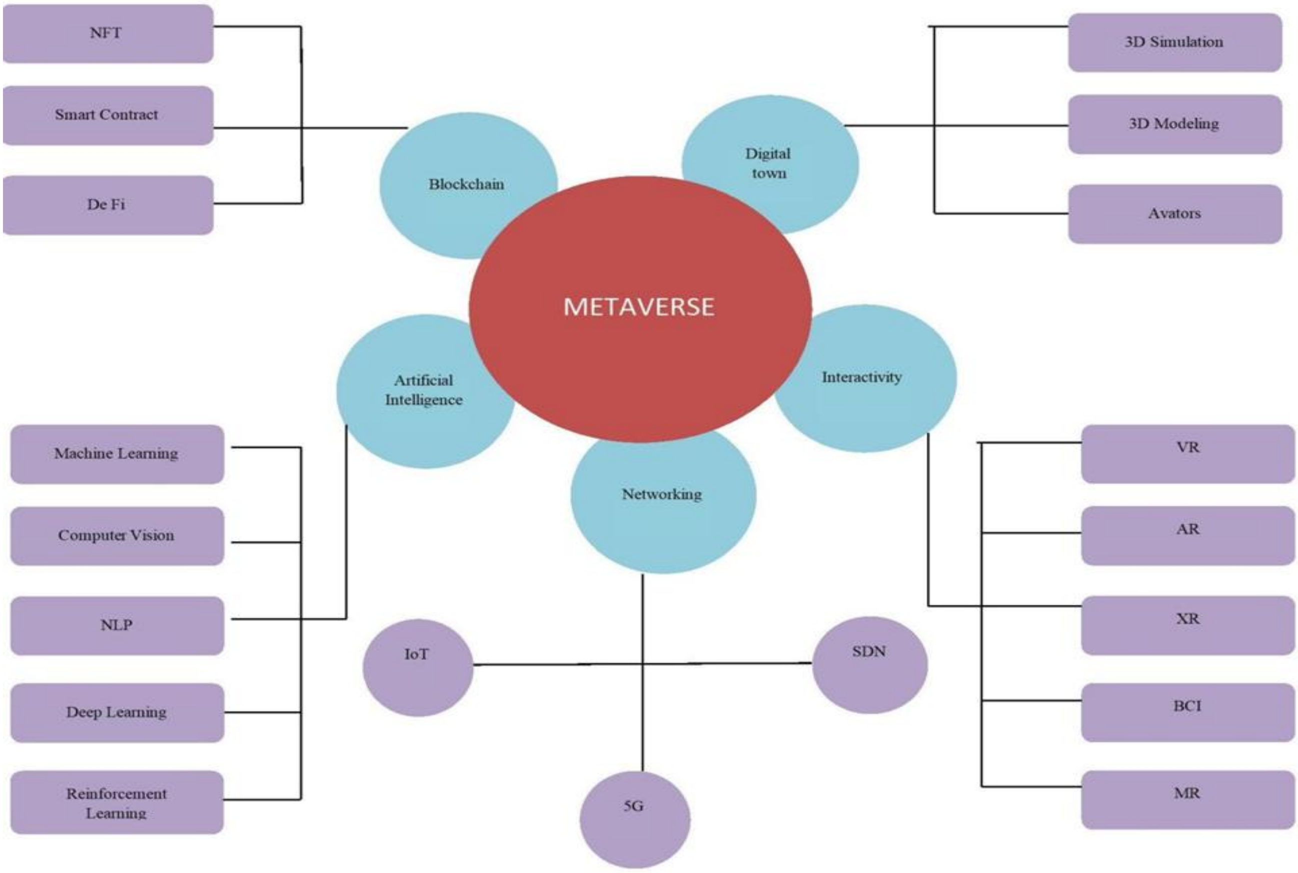

Figure 1: Applications of the Metaverse

Furthermore, the Metaverse has growing potential for medical training and education. Without endangering people, it enables medical students and healthcare professionals to hone their skills in a realistic virtual environment [12]. The Metaverse is a whole new digital environment where people can engage in a variety of activities [15]. The use of the Metaverse to improve medical image processing, improve healthcare collaboration, improve access to care, and improve the efficiency of medical services has grown in popularity over the past few years [17]. Nevertheless, numerous technical challenges must be overcome before the Metaverse can be fully integrated into medical imaging processing. This essay will discuss some of the most important considerations before the Metaverse can be effectively leveraged for medical imaging processing [9]. Privacy and security of patient data represent one of the greatest hurdles. The security of patients' medical images is protected by a number of laws and regulations that safeguard patients' privacy [10]. In the Metaverse, without additional safeguards, these images are highly likely to be easily compromised or hacked, leading to a multitude of issues for patients and healthcare providers [11]. Thus, for the Metaverse to be used for medical imaging processing, securing the transmission and storage of medical imaging data is a critical concern. Another significant consideration is how to integrate medical image data with the Metaverse. Medical images typically contain significant data and may therefore require substantial processing power and bandwidth for transfer and processing [13]. An example of medical image analysis using deep learning is shown in Figure 2.

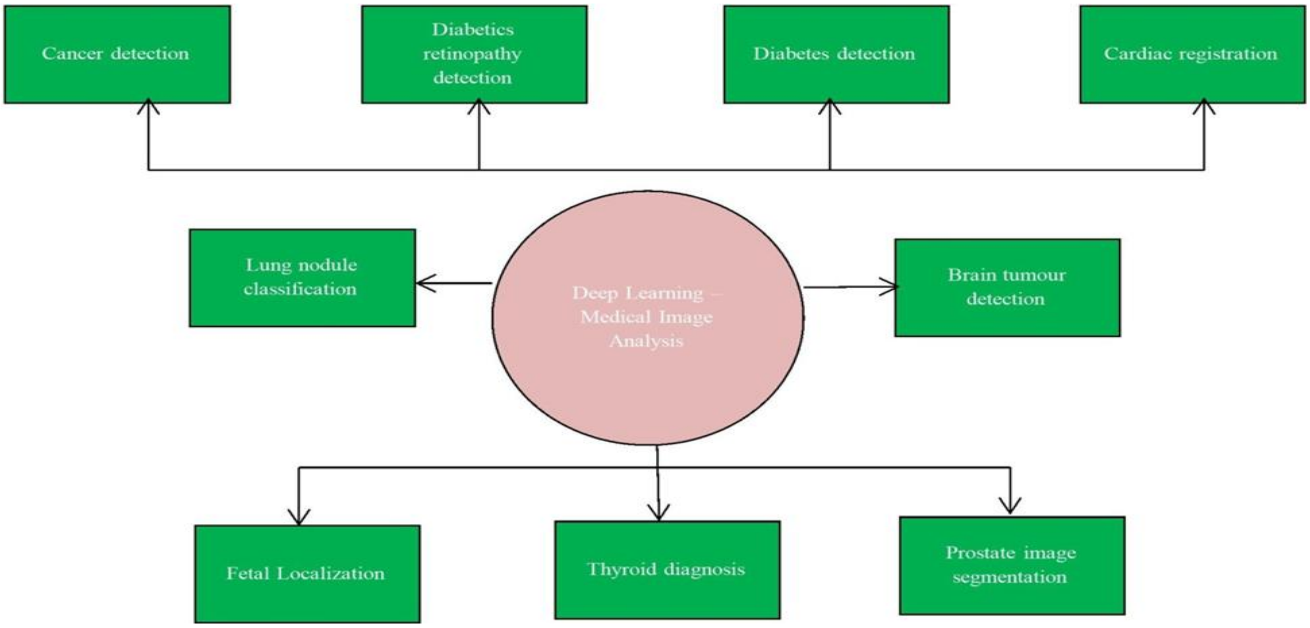

Figure 2: Applications of deep learning medical image analysis

Medical imaging often contains intricate designs that must be evaluated with specialised equipment [14]. Thus, to integrate these medical images into the Metaverse, researchers require new technologies and infrastructure, which create additional technical hurdles and standardization and compatibility issues. Countries develop different medical imaging technologies and methods of recording them within their healthcare system [16]. For the Metaverse to function well in medical image processing, researchers require standardized methods for acquiring, storing, and analyzing images to enable interoperability among systems and devices, enabling efficient, secure data exchange [18]. Currently, there are no established protocols or guidelines for using metaverse technology to process medical images; these include ethical and legal considerations, as well as best practices for data management and analysis. Using medical images without clear guidelines and rules can lead to abusive practices and raise both ethical and practical issues within the Metaverse [19]. Although there are many opportunities arising from the use of the Metaverse to process medical images, many technical obstacles need to be addressed before this technology can be fully utilized within healthcare [20]. The four fundamental areas that need to be addressed include data privacy and protection, integration of the medical image data, standardising and ensuring compatibility with each of these images, and finally, developing protocols and guidelines surrounding the most efficient way of using the Metaverse for medical purposes:

- **Improved Visualization and Analysis:** One of the main research contributions of adopting metaverse technology in medical image processing is the development of improved visualization and analysis techniques. The incorporation of medical imaging into the virtual world provides an immersive way for doctors and researchers to engage with and work on medical images, improving their comprehension of the data and increasing the accuracy of their diagnoses.
- **Facilitated Collaboration/Communication:** By providing access to the same 3D virtual environment, Metaverse technology enables more effective communication and collaboration among medical professionals. Doctors and researchers can collaborate more effectively on patient cases while remaining in different areas of the world, thereby making better, timelier decisions and treatment plans.
- **Education/Training of Professionals:** The introduction of Metaverse Technology into medical image processing has also improved the education and training of medical professionals. Medical students and residents will have the opportunity to interact with and learn from 3D Medical Imaging data through an immersive, interactive virtual environment. The MedaVerse provides medical students and residents with the opportunity to learn valuable skills that will benefit their careers as they progress into their professional practices. Another significant benefit of implementing metaverse technology in medical imaging is increased ease of use and greater movement options. The ability for medical professionals to use virtual devices, such as headsets, and to have instant access to 3D imagery from any location enables them to operate remotely while providing support and/or diagnostic assistance to patients. This technology also offers a new opportunity to improve medical procedures through the creation of advanced, progression-based simulations, which facilitate best-practice training for physicians, including virtual surgical planning before executing a procedure. The ability to “virtualise” the anatomy leading up to a surgical procedure using 3D modeling tools provides an opportunity to improve patient safety and achieve optimal financial outcomes compared to traditional training methods.

2. Related Works

Chen and Zhang [21] in their “Bibliometric Analysis of Current Research Trends on Emerging Technologies in the Health Metaverse” conducted a bibliometric study that identified critical health metaverse research areas, as well as the contributions made by different countries and institutions and the most highly cited authors with the most significant interaction networks of collaborators; thus providing useful knowledge to other researchers and developers who will work on this new field of research. Atalay and Sönmez [22], in the paper “Digital Twins in Health Care” in their edited book “Digital Twin- Driven Intelligent Systems and Emerging Metaverse,” explained how digital twin technology can be used in various ways in the healthcare industry, such as for remote patient monitoring, predicting patient diagnoses, and providing personalised treatment plans for individual patients. Qiao et al. [23] referred to the developing “Sprechd” technology as being based on neural networks designed to recognise fetal congenital heart disease in the medical Metaverse using a 4-chamber semantic parsing strategy and to demonstrate that it can accurately classify and identify heart defects. The hope is that the Sprechd technology may provide a new tool for the early detection and prompt treatment of these congenital heart defects. Xu et al. [24] described the edge-enabled Metaverse as the immersive experience enabled by advances in edge computing and the implementation of Fifth Generation (5G) networks. The Metaverse offers enormous potential across many industries while presenting challenges related to safety, security, user experience, and other key aspects of individual use. The authors JFS Jagatheesaperumal et al. [25]. In an age of rapidly developing technologies, the metaverse and AR/VR/XD (extended reality) technologies, combined with the Internet of Everything (IOE), enable a truly innovative form of education. A few challenges and unanswered questions remain about the use of AI in education, particularly regarding its accessibility and ethics.

To maximise the current advantages (benefits) of technologies like AI and 6G to our global education system, continued research needs to occur [26]. This research highlights the emerging combination of AI and 6G as it relates to the expanding Metaverse, noting many opportunities and potential obstacles associated with the growth of these technologies. Further, Wu et al. [27] examined the impact of 6G technology on Healthcare Analytics Through the Metaverse. They provided insight into how the technology will enable real-time anomaly detection for Internet of Things devices and improve patient care by enhancing the effectiveness and efficiency of healthcare systems overall. Utilizing emerging technologies, such as augmented reality shopping tools, as well as immersive and cognitive technologies, image processing, and object-tracking algorithms, has changed how consumers shop in the Metaverse, allowing them to interact with the virtual products they want to purchase in an engaging, visually compelling manner. Additionally, the potential of the Metaverse to redefine and change the existing hospital, clinic, and healthcare sectors is evident; through the use of the aforementioned technologies, telemedicine and training simulation applications have become viable options in the medical community. However, as noted by Farahat et al. [29], privacy concerns and the need to expand access for disenfranchised communities pose challenges to the use of the Metaverse. Lifelong Learning in the Edu-Metaverse is a newly established framework utilising both technology and conventional education to create a truly interactive and engaging space for students and instructors to connect. The goal is to educate better, prepare people for the future, and promote a lasting interest in the field of education. Grupac and Lăzăroiu [31] have discussed how these experiences can empower individuals and provide the necessary tools to improve the educational experience. The economy of the Metaverse is supported by cutting-edge technologies, including analytical tools that convert graphical information into high-resolution imagery, tools that extract useful insights from sensory data, and forecasting models of people's purchase behavior.

These innovations will enable quick processing of graphical imagery, identify and leverage opportunities by analyzing relationships between different types of data stored in multiple ways (across a variety of computers/storage devices), and predict customer behavior. In the coming years, as the Metaverse becomes increasingly used and accepted by health and medical professionals in their respective fields, it will greatly alter how care is delivered, trained for, conducted, and even prepared for. As the Metaverse continues to grow in size and influence, Khang et al. [33] discuss how this growth will create a new frontier for a traditionally conservative industry such as the health industry. By leveraging VR and AR technologies to deliver more immersive, engaging, and enjoyable experiences to patients, medical professionals, and their families, the positive effects will be felt across many aspects of how health care is delivered, improved, and received. The application of AI technology in the health and wellness fields, as discussed by Bibri and Jagatheesaperumal [34], has highlighted an avenue that companies working with the Internet of Things (IoT) have also explored and utilized. Through the combination of affordable XReality technologies and synergistic AIoT systems, innovative new ways to connect patients with their healthcare providers and support their daily lives are now being developed and employed. By improving connections and increasing productivity in cities, a more advanced, sustainable, and innovative city will be created in the future, according to Perkins [35]. The emergence of computer vision and AI technology has enabled algorithms for object detection and virtual retail. Immersive, realistic virtual reality experiences can now occur in 3D space, like the Metaverse, thanks to this development. The technology involves both simulation and spatial data-gathering methods to replicate “real”- world environments [36]. The Metaverse is a burgeoning digital world with great potential for medical education, research, and the delivery of patient care.

The Metaverse has opened new avenues for virtual simulation, communication, and data analysis, enabling more efficient and comprehensive healthcare delivery and maintaining a continuum of care. Each day, the healthcare industry becomes more advanced through technological developments and continues to provide services to those who need care [37]. The DAVE platform uses deep learning algorithms to create asymmetrical, immersive virtual environments for products in the Metaverse, enabling users to experience them in a realistic, customized way. By employing state-of-the-art technologies and experience-based design, DAVE provides all users with an exciting, unique experience in the Metaverse. According to Agac et al. [38], this paper analyses the evolution of research on the use of metaverse-based technology to teach health-related topics. Emerging research trends and hotspots in this area suggest there are many opportunities to conduct further research and to find ways to utilize the Metaverse for health education. A bibliometric analysis of research papers provides additional quantitative evidence. Joshi and Pramod [39] have explained that CO-MATE is a collaborative, hybrid platform that provides a combined virtual and real-world learning experience, combining the two types of learning; therefore, students can learn and advance through these multiple avenues. Musamih et al. [40] have stated that the Metaverse can positively impact health care by providing virtual environments for educating patients, training clinicians, and researching medicines; however, several issues, including data security, access to services, ethical concerns, and digital health records not being compatible with current systems; therefore, steps should start to develop immersive and accessible experiences to improve health care results. Table 1 provides a SWOT analysis for several of the papers reviewed.

Table 1: SWOT analysis

Author	Advantage	Limitation
Chen and Zhang [21]	Provides insights into the impact and potential of emerging technologies in shaping future healthcare practices.	A limited number of publications are available for analysis due to the relatively new concept and emerging nature of the health metaverse.
Atalay and Sönmez [22]	One advantage of Digital Twins in healthcare is improved patient outcomes through personalized treatment plans and virtual collaboration between patients and healthcare providers.	Limited accessibility for low-income communities due to high costs and tech requirements for implementing Digital Twin in healthcare systems.
Qiao et al. [23]	Efficiently identifies and categorises congenital heart disease in fetuses, enabling earlier intervention and improved patient outcomes.	Only applicable to fetal congenital heart disease recognition, not suitable for other medical conditions.
Xu et al. [24]	Efficient real-time data processing and analysis for seamless user experience and increased immersion in the Metaverse.	Limited accessibility for individuals with physical or financial limitations.
Jagatheesaperumal et al. [25]	Increased accessibility to education for individuals in remote or under-resourced areas through virtual learning platforms.	The high cost of technology and access may limit availability and reach.
Zawish et al. [26]	More efficient and personalised virtual experiences for users.	Lack of real-world implementation and practical use cases leads to speculation and theory-based research.
Wu et al. [27]	Improved detection and prevention of potential anomalies in healthcare data, leading to better patient outcomes and overall efficiency in healthcare operations.	A lack of real-time monitoring capabilities may delay response time to anomalies in the healthcare setting.
Grupac et al. [28]	Increased customer engagement and personalized shopping experiences, resulting in higher conversion rates and customer satisfaction.	Limited accessibility and compatibility for low-end devices or slower internet connections.
Farahat et al. [29]	Improved access to specialised healthcare services and resources for patients, regardless of geographical location.	Technology barriers may limit access and effectiveness, particularly for older and marginalised populations.
Wang et al. [30]	Increased engagement and motivation for learning as students are immersed in a dynamic and interactive virtual environment.	Limited adoption or integration due to resource constraints or technological barriers.
Grupac and Lăzăroiu [31]	“Enhanced decision-making capabilities for businesses through advanced data analysis and forecasting in the metaverse economy.”	Reliance on data privacy laws to ensure accurate customer targeting may limit the effectiveness and ethical use of these technologies.
Wu et al. [32]	Potential for improving medical education, training, and simulations through immersive experiences in a virtual Metaverse environment.	Researchers are missing potential connectivity, adoption, and scalability concerns across healthcare settings.

Khang et al. [33]	This handbook provides comprehensive coverage of AI-based technologies and their applications in the emerging Metaverse, preparing readers for this new paradigm.	Possible limitation: Limited coverage of specific emerging technologies and their applications in the Metaverse.
Bibri and Jagatheesaperumal [34]	Through Metaverse and AI integration, augmented reality and smart technology can be implemented more efficiently and affordably in urban areas.	Reliance on advanced technology and high costs may limit the widespread adoption of the systems in urban areas.
Perkins [35]	It allows for enhanced customer experience and immersive interactions with products, leading to increased sales and customer satisfaction.	High costs may limit the accessibility and widespread use of these technologies in extended reality environments.
Suh et al. [36]	Improved accessibility and inclusivity for patients and medical professionals, resulting in better, more efficient healthcare outcomes.	Limited accessibility for people with limited technological skills and resources.
Cho et al. [37]	Offers highly realistic, dynamic virtual environments for an immersive, engaging metaverse experience.	Dependence on technology access and barriers to entry may limit widespread adoption and participation by diverse demographics.
Agac et al. [38]	"Provides a comprehensive overview and understanding of key areas for potential innovation and advancement in health education using metaverse technology."	Limited by the availability and scope of data used in the bibliometric analysis.
Joshi and Pramod [39]	Flexibility: Enables students to have more control over their learning experience by choosing their own learning modules and pathways.	Dependency on technological infrastructure and user proficiency may hinder universal access and adoption.
Musamih et al. [40]	Improved access to medical and telehealth services for remote and underserved populations.	Lack of widespread implementation and adoption due to technological and regulatory barriers.

2.1. Identified Issues

- **Privacy and Security Issues:** The fact that the Metaverse is based on the interaction of individuals in a virtual environment and the exchange of data raises concerns about how to protect sensitive health information and ensure secure methods for communicating it.
- **Technical Infrastructure:** The ability to support effective adoption of Medical Image Processing in the Metaverse requires establishing a robust infrastructure, including a stable, high-speed Internet connection, server capacity, and hardware. A stable, reliable technical infrastructure will help ensure the high quality of medical image processing delivered in the Metaverse.
- **Integration:** Many medical centres have already built systems to manage the storage and processing of Medical Images. Adopting the Metaverse for Medical Image Processing will require an easy, seamless integration with the facilities' existing systems; this will minimize disruption and allow facilities to maintain continuity of their data.
- **Standardization of Formats and Protocols:** Standardizing medical image processing formats and protocols is essential for successful use in the Metaverse, enabling interoperability across diverse medical image processing systems/devices and facilitating seamless communication and collaboration.
- **The Precision/Quality of Medical Image Processing:** For the medical image processing algorithms used within the Metaverse to be of the highest quality and accuracy, it is necessary to ensure that any algorithmic fault or error will not negatively impact a patient's care. Thus, before medical image processing algorithms are used in the Metaverse, they must be rigorously validated through extensive testing.

2.2. Objectives of the Research

- **High-throughput Processing of Big Image Datasets:** A framework that meets high-throughput processing needs at the lowest possible computing cost will increase the acceptance of using a metaverse for processing medical images.
- **Deep Learning Algorithms for Robust Analysis of Medical Images:** A framework should include advanced methods for applying Deep Learning to analyze medical images accurately. The framework will provide better results when there are many types of image variation (noise, artifacts, etc.) and across different patient populations.
- **Real-Time Processing of Medical Images:** Real-time processing will enable quicker diagnosis and treatment. A framework designed for the medical industry will strive for real-time medical imaging.

- **General User-Friendly Interface:** A user-friendly interface that is simple enough for people at different skill and expertise levels to use the framework will help facilitate its acceptance as a new tool in the medical community.
- **Multi-Modality Medical Imaging:** A framework should be able to operate across the various modalities (MRI, CT, Ultrasound, and X-ray) used in different settings within the medical community. A multi-modal framework will make the work processes more efficient and thereby provide superior patient care.

2.3. Novelty of the research

- **The Incorporation of State-of-the-Art Deep Learning Methods:** The advanced framework will use the latest deep learning methods, such as transfer learning, generative adversarial networks (GANs), and reinforcement learning, to improve feature extraction and information representation from medical Images, resulting in better performance on extremely complex tasks.
- **Use of a Virtual or "Metaverse" Environment During the Medical Imaging Process:** By using a virtual/mixed reality/metaverse type of environment during the course of the medical imaging process, the advanced framework allows users to more quickly and more effectively perform their job functions with the medical Imaging data, and to include virtual/augmented reality technologies in the workflow.
- **The Development of an Optimized Advanced Framework Specifically for Medical Imaging:** Several existing deep learning frameworks have been developed as general-purpose tools. Therefore, the advanced framework was created specifically to address the unique challenges and needs for medical Imaging Data, such as the management of large, diverse data sets, filtering out too much noise and incomplete physical imaging-based Medical Data Sets, and giving users of medical imaging the best possible accuracy with complete reliability when performing diagnoses.

3. Proposed Model

Deep learning approaches are becoming increasingly popular in medical image processing. They have increased the precision and effectiveness of prognostic (predicting the course of a disease and the likelihood of dying from it) and diagnostic (diagnosing a disease or sickness) models. Nevertheless, the applications of existing frameworks are limited because they do not fully exploit the richness and complexity of information in medical images. This research suggests a novel deep learning method to overcome these challenges, a framework that will use a combination of several deep learning models, all with different architectures designed with specific key characteristics of medical imaging. By utilizing multiple models together and combining their outputs, the proposed approach will allow the model to be more flexible and adaptable, and ultimately achieve better performance across a wider array of medical image processing tasks. Additionally, the proposed framework incorporates transfer learning to enable faster model training, with the potential to improve generalization from limited training data.

3.1. Construction

A machine learning model's training stage describes how the model extracts patterns from the given dataset to build a model that can be applied to other datasets in the future. There are other phases within the Training Stage. A data set that offers pertinent information and comprehensive raw data on the needs of the training data set is known as historical data. The numerous characteristics of historical data are all pertinent to the model's requirements as it prepares to use real or comparable data during the Training Stage's Performance Testing phase. Typically, databases, sensors, or other raw data streams that could provide information for machine learning models to forecast future events are used to gather historical data over the course of a month. Metaverse, within the framework of Machine Learning, is another environment that allows integration and analysis of multiple Historical Data Sets. Data sets may be represented in multiple ways to visualize and study their relationships. The real-world environment wherein the machine learning Model will operate and be tested with actual data. At times, the Real-World environment also includes live or near-real-time data and events that the machine learning Model must analyze and predict. The Pre-Processing step in the Training Stage is an important step, during which raw or unorganized data is converted into organized, reusable datasets used to train the machine learning Model.

Noisy data and missing values are eliminated, and the data is transformed into an appropriate format for the training algorithm during Data Fusion, which combines datasets from multiple sources into a single unified dataset to enable a complete understanding of your problem and, as such, improve model accuracy. A proposed example of a constructed model is illustrated in Figure 3. A model will be trained by feeding it prepared data to learn the patterns and relationships between various features. The algorithms or techniques to use will depend on the type of problem being solved (e.g., classification or regression) and the type of data available. The goal of training is to optimize the model's parameters and improve overall accuracy. Model output is the result of the training phase: the resulting Training Model contains what the machine has learned about the data, along with how it has learned to reveal those patterns and relationships when it makes future predictions on new data. Evaluating/testing the trained model against a dataset not included in the training process; this is called Testing. Testing a trained model provides an assessment of performance and can reveal areas that may need improvement or help identify problems within the model. Understanding how the model makes predictions is called Model Reasoning; the reasoning process involves examining the patterns or relationships the model has learned and interpreting its predicted output.

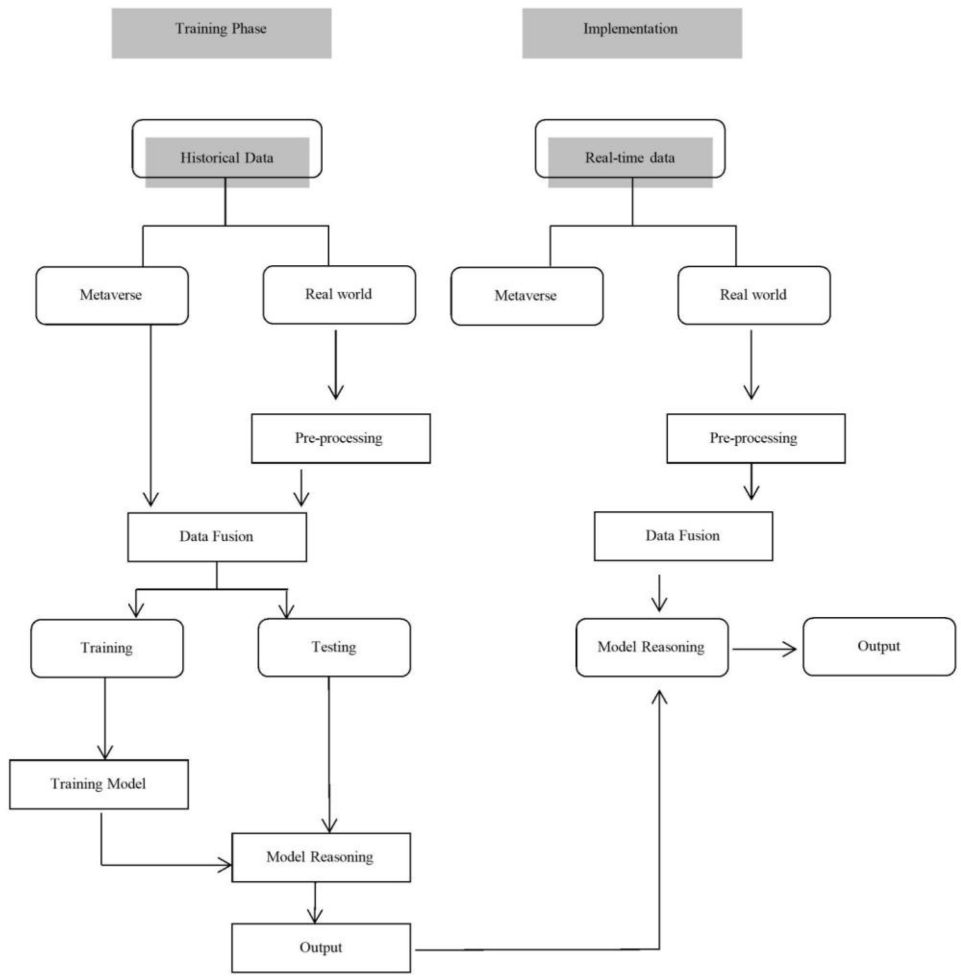

Figure 3: Construction of the proposed model

Output is the result of the Training Model's predictions on new input data. The output can help inform and assist in decision-making to solve real-world problems across many areas, including Healthcare, Finance, and Marketing. To implement the training phase successfully, it can be done within the bounds of the real world, both within the confines of a Metaverse and through real-time data. With the advent of Real-Time Data, you can continually add new data to your model as it becomes available, enabling it to make precise forecasts and adjust to shifting trends. You may train and test your machine learning by combining and analysing various data kinds from various data sources in a single virtual environment, thanks to the Metaverse. model. When you've developed a machine-learning model through training, you can apply it to live data streams from the Real world to make real-time predictions to assist in informing your decision-making processes. The Training phase is a fundamental step in building a machine learning model. It consists of using Historical, Metaverse, or Real-World Data to train the model to produce Accurate Predictions. During the Training phase, Data undergoes three stages of Data Transformation (Pre-processing, Data Fusion, and Training) before the model is evaluated and ultimately used to assist in decision-making and guidance. Proper application of the Training phase ultimately results in the creation of Accurate and Reliable Machine Learning Models, which in turn will enable you to solve Complex Problems in Many Different Areas.

3.2. Operating Principle

The process of Data Selection refers to the activity of carefully selecting relevant data from a larger dataset that you wish to analyse. In this phase, you will identify which variables and/or characteristics of the data are most important for the task at hand; this is critical to avoiding bias and ensuring your results are valid. The process of how you will organize and present your data to perform Analyses is known as Data Representation. This is important so that you will have an organized, easily understood format for raw data that a computer can use to perform various analyses. Since Data Representation is a necessary step before performing data analyses, it is important to represent your data in a manner that is most effective for storage, manipulation, and visualization. The process of selecting the most important features (or variables) from your dataset for use in a predictive model is called Feature Selection. By selecting the best features, you can reduce the predictive model's overall complexity while improving its performance. Selection of features should include those most likely to affect the predicted result and those highly correlated with the Target variable. Once the features of the dataset have been selected, Training Set Binding must occur, which binds the selected features to the dataset's Target variable.

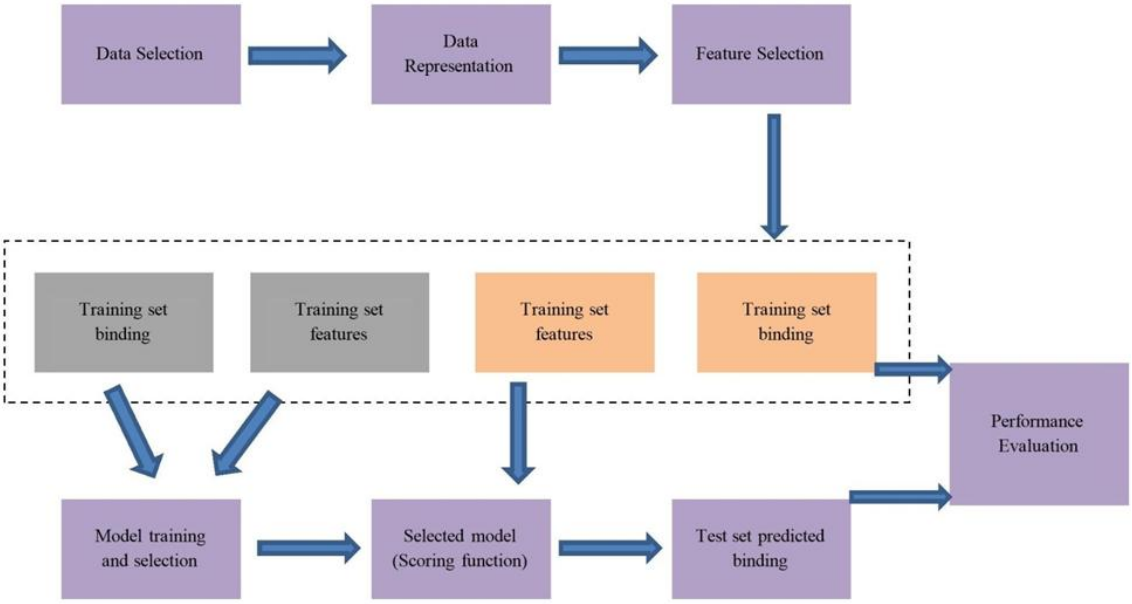

Figure 4: Operating principle

From here, a subset of your dataset, known as the Training Set, is created to teach the model how to make accurate predictions based on the selected features. Training set features are the actual attributes included in the training set. These are the features used for training models and represent a carefully selected part of the training set to ensure the model can accurately predict the target feature. Once the model and a suitable machine learning algorithm are selected, model training and selection consist of using this data to “train” the algorithm, adjusting the model's parameters to achieve optimal performance. A model selected from the previous steps should be able to generalize to new datasets and produce accurate predictions for the target feature.

The way our proposed model operates is shown in Figure 4 of the paper. The selected model (Scoring function) is the one chosen based on its performance during training. This model is used to make predictions on new data, and its accuracy is evaluated using a scoring function. By averaging the pixels, the Average method is a fusion technique that merges images. This method focuses on every aspect of the image, and it functions properly if the photographs are taken using the same type of sensor:

$$F(x,y) = \frac{p(x,y)+Q(x,y)}{2} \tag{1}$$

$$F(i,j) = \sum^{M}{}_{i=1} \sum_{j=2}^{N} max\, A\,(i,j)B(I,j) \tag{2}$$

In it, the minimum equivalent pixel intensity between the two input images is selected to produce the fused image's outcome. Using image processing software is essential to decompose a picture into its component sine and cosine:

$$F(k,l) = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} f(i,j) e^{2\pi} \left(\frac{ki}{N} + \left(\frac{lj}{N}\right)\right) \tag{3}$$

$$f(a,b) = \frac{1}{N2} \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} F(k,l) e^{-2\pi} \left(\frac{ka}{N} + \frac{lb}{N}\right) \tag{4}$$

The above problem must be solved by computing a double sum from a specific perspective to obtain the desired outcome. Nonetheless, the Fourier Transform could be utilised independently and explained as follows because it appears to be separable:

$$F(k,l) = \frac{1}{N}\sum_{b=0}^{N-1} P(k,b)e^{i2\pi\frac{lb}{N}} \tag{5}$$

$$P(k,b) = \frac{1}{N}\sum_{a=0}^{N-1} f(a,b)e^{i2\pi\frac{ka}{N}} \tag{6}$$

Because DCT may decorrelate image pixels, it is an effective image compression technique:

$$X_k = \frac{1}{2}(X_0 + (-1)X_{N-1}) + \sum_{n=1}^{N-2} X_n \cos\left(\frac{\pi}{N-1}nK\right) \tag{7}$$

$$X_k = \sum_{n=0}^{N-1\Sigma\left[\frac{\pi}{N}\left(n+\frac{1}{2}\right)K\right]} X_n cos \tag{8}$$

$$\frac{1}{\sqrt{a}}\sum\sum f(x,y)\Psi\left(\frac{x-m}{a},\frac{y-n}{b}\right)dxdy \tag{9}$$

$$MSE = \frac{1}{M*N}\sum_{t=0}^{M-1`}\ \ {}_{j=0}^{N-1}[I(i,j) - K(i,j)]^2 \tag{10}$$

The scoring function measures how well the model has learned from the training set and how accurately it can predict the target variable. Test set predicted binding uses the trained model to forecast a different dataset that wasn't used during training. This is done to assess how well the model performs on unseen data and ensure it generalizes. Performance evaluation involves assessing the accuracy and effectiveness of the selected model by comparing its predictions on the test set to the actual values. In the field of computer-aided diagnosis in medical image analysis, several methods are used to improve the performance of these types of systems. One method is to use deep learning architectures, such as Encoder-Decoder Networks.

3.3. Encoder and Decoder

The purpose of using an Encoder-Decoder architecture is to produce an output (Segmentation map) from an input medical image by accurately segmenting various structures or abnormalities. The Encoder-Decoder architecture consists of two major sections: The Encoder section performs Feature extraction on the input image, while the Decoder section uses features generated by the Encoder to create a User Segmentation map. The accuracy of the Segmentation map will depend on the quality of the input medical image. Generally, to enhance the quality of the input image, the "Weak Aug" technique is used. "Weak Aug" refers to various image processing techniques that modify existing medical images by creating multiple variations from the original input(s) to improve robustness and mitigate overfitting. Some examples of weak augmentation techniques include random rotation, translation, and adding noise to the input image. The construction of the encoder and decoder is shown in Figure 5.

Contrarily, "Stronger Augmentations" refers to using more intensive image augmentations to create larger differences compared with the inputs to the model (other than merely resizing as was the case in "Basic Augmentations") by employing such operations as flipping horizontally/vertically, scaling up/down, and cropping the original input images. These more aggressive augmentations can be classified as extreme; however, they have been shown to improve the accuracy of Deep Learning models when applied to Medical Imaging datasets. The MSE is zero if it finds two identical photos. For this number, the PSNR is undefined (zero divided by zero). Given that a division-by-zero error causes the MSE to become zero, an identical image yields an uncertain PSNR:

$$PSNR = 10\,log_{10}(peakval)\,MSE \tag{11}$$

$$MSE = \frac{1}{MN}\sum\left(f(x,y) - f(x,y)\right)^2 \tag{12}$$

It is comparable to a multi-input, single-output nonlinear threshold device. Describe the neuron's input vector:

$$A = [A_1, A_2, A_3, \ldots., A_n]^T \tag{13}$$

$$\varepsilon = [\varepsilon_1, \varepsilon_2, \varepsilon_3, .., \varepsilon_n]^T \tag{14}$$

$$B = \left(\sum_j^N A_j\varepsilon_j + \partial\right) \tag{15}$$

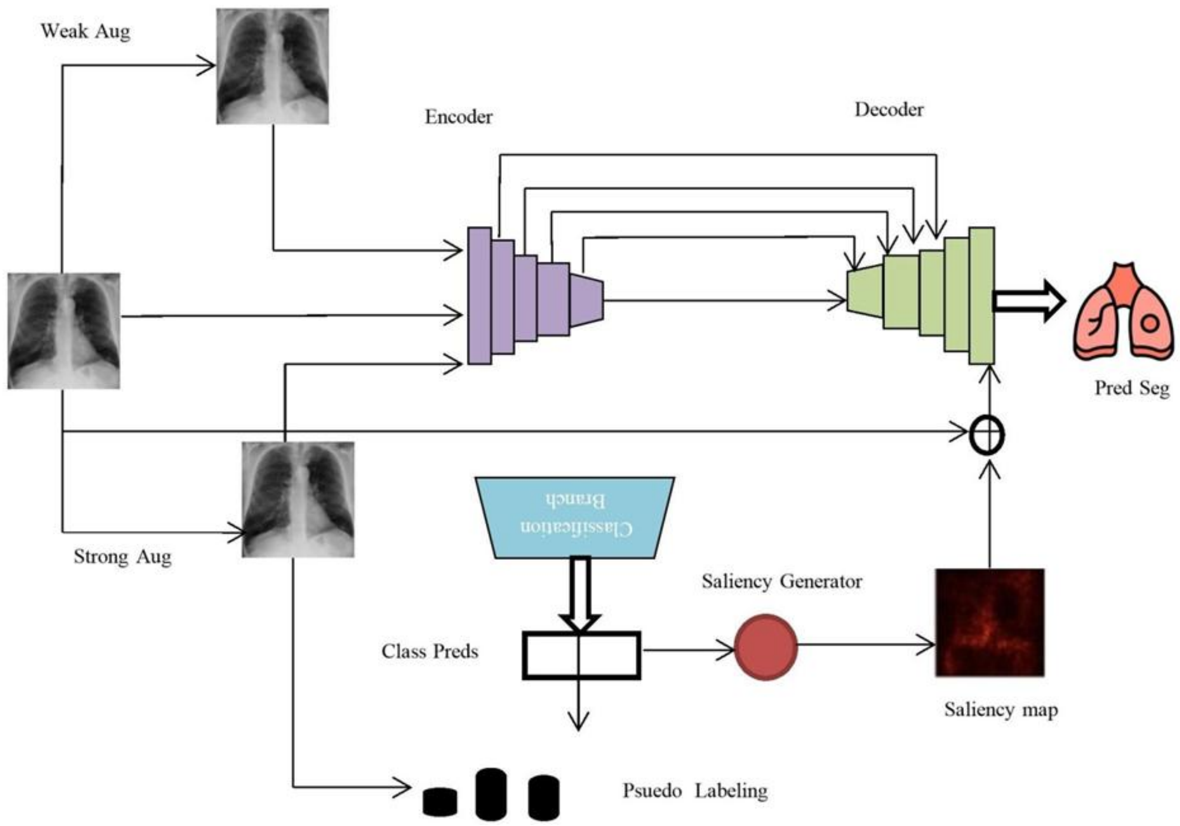

Figure 5: Construction of encoder and decoder

To evaluate the segmentation map prediction, the encoder-decoder architecture's output must be evaluated using the Classification Branch. The Classification Branch classifies the Detection decoder output as various classes or abnormalities. As a result, the Classification branch adds accuracy to the segmentation map by confirming that the segmentation is correct and that the model correctly identifies the anatomical structure in the medical images. The second method for enhancing the accuracy of a segmented map is pseudo-labeling. Pseudo labelling refers to a technique whereby the model's prediction can be utilised as labels for the images and retrain the model using these pseudo labels as well:

$$p(x,h) = \frac{e^{-energy(x,h)}}{z} \tag{16}$$

$$p(x) = \sum_h p(x,h) = \sum_h \frac{e^{-energy(x,h)}}{z} \tag{17}$$

$$p(x) = \frac{e^{-freeEnergy(x)}}{z} \tag{18}$$

$$FreeEnergy(x) = -\log \sum_h e^{-energy(x,h)} \tag{19}$$

$$\frac{\partial \log p(x)}{\partial \theta} = -\frac{\partial freeEnergy(x)}{\partial \theta} \tag{20}$$

$$E_{\hat{p}}\left[\frac{\log p(x)}{\partial \theta}\right] = -E_{\hat{p}}\left[\frac{\partial freeEnergy(x)}{\partial \theta}\right] \tag{21}$$

$$D_i = F(Qx_i + B) \tag{22}$$

$$\widehat{x_i} = F(Q'x + A) \tag{23}$$

In this technique, correcting past errors enables the model to improve its forecasts and perform better in future forecasts. The feature extraction is outlined in Figure 6.

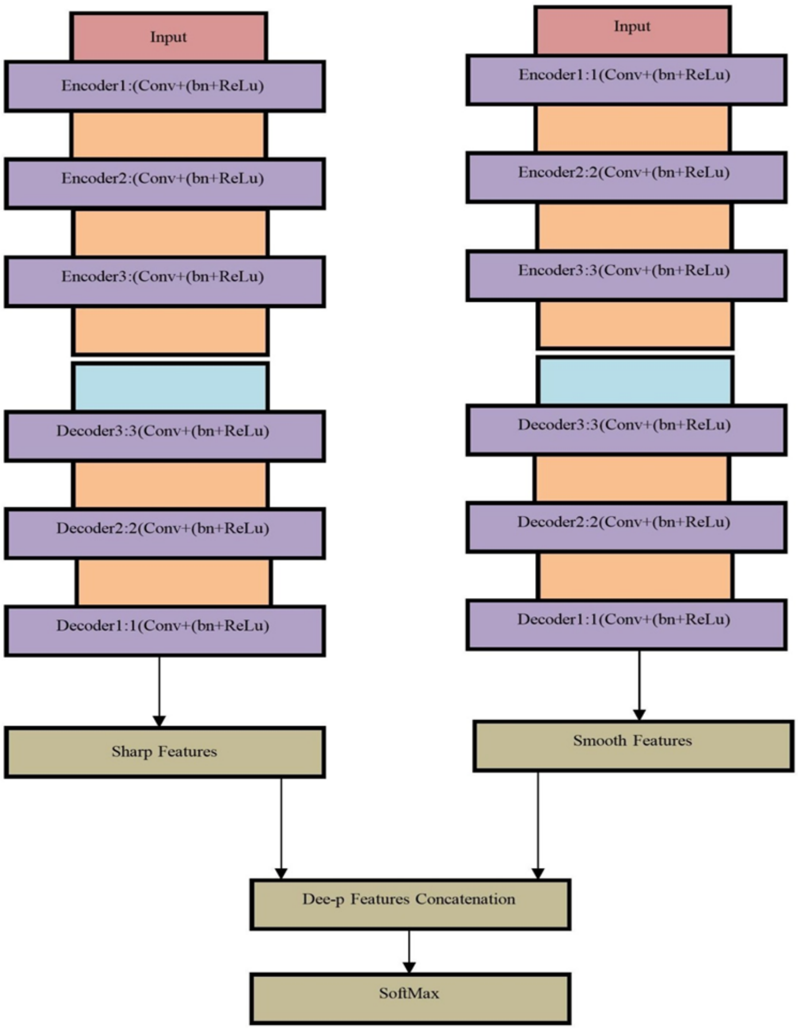

Figure 6: Feature extraction

The saliency generator is another aspect of the encoder-decoder framework that can improve the accuracy of the segmentation map. Saliency maps are visual representations of the areas of a medical image that stand out as crucial. A guideline for locating the most vital features and structures of the input medical image is provided by using saliency maps during the prediction process, thereby enabling more accurate predictions by the model. Currently, the input layer is being converted to the output layer using the sample data, which illustrates the overall process of execution for the model, as given below:

$$U_v = g_n(\ldots(g_2 g_1(A_v T^1)T^2)T^n) \tag{24}$$

$$E_v = \frac{1}{2}\sum_{j=1}^{n}\left(B_{vj} - U_{vj}\right)^2 E = \sum E_v \tag{25}$$

In deep learning for feature extraction, sharp and smooth features are among the most commonly used techniques. Both of these types of features have been developed to capture the essential characteristics and patterns in input data and improve the ability of the neural network to learn about this data and predict accurately:

$$A = (a_1, a_2, \ldots, a_o) \tag{26}$$

$$R = \left(r_1, r_2, \ldots., r_p\right) \tag{27}$$

$$B = \left(b_1, b_2, \ldots, b_q\right) \tag{28}$$

$$C = \left(c_1, c_2, \ldots, c_q\right) \tag{29}$$

Sharp features characterise local variations and abrupt changes in the input data. Sharp features can be seen as high-frequency components of input data, represented by sharp edges and corners in images or sudden changes in time series data. Sharp features are typically derived using convolutional layers, which are augmented with batch normalization and ReLU activation. While batch normalization stabilizes the training process by normalizing the input to each layer, convolutional layers use tiny kernels to capture spatial relationships in the input data. The network's non-linearity is further improved by the ReLU activation function, which enables it to capture more intricate features. To extract high-level crisp features from the input data, encoder layers of a deep neural network stack several convolutional layers:

$$S_j = g\left(\sum_{i=0}^{o} W_{ij} A_i + \varphi_j\right) \tag{30}$$

$$B_m = g \sum_{j=0}^{p} T_n R_j + \varepsilon_m \tag{31}$$

$$g(A) = \frac{1}{1+E^{-md}} \tag{32}$$

Since it helps to increase contrast, it is especially helpful in the field of medical imaging, especially when the contrast values of the ROI and its surroundings are similar:

$$CAI = \frac{C_{processed}}{C_{autual}} \tag{33}$$

$$IAC = \frac{m-s}{m+s} \tag{34}$$

Where IAC is the image area contrast. It was able to obtain the frequency and spatial data. The GFB produces three different types of characteristics: Amplitude, phase, and direction. In these filter banks, a Gaussian envelope is modulated by a sine plane wave:

$$S(x,y) = \frac{f_c^2}{\pi t n} e(f_n^2 t^2)x^2 + (f_n^2 n^2)y^2 e^{j2\pi f_c^x} \tag{35}$$

$$x' = x \cos \theta_d + y \sin \theta_d \tag{36}$$

Researchers use both t and n to calculate the ratio of the centre frequency to the size of such a Gaussian envelope:

$$G_{c,d}(x,y) = I(x,y) * S_{c,d}(x,y) \tag{37}$$

This criterion can occasionally be satisfied by ensuring that the characteristic quantities of the learned policy match those of the observation:

$$\forall j \in \{1, \ldots, L\} \sum_{p \in P} T\left(\frac{\tau}{\pi, P}\right) e_j^P = \hat{e}_j \tag{38}$$

$$T_s\left(\frac{\tau}{\theta, P}\right) \alpha c_o(r_1) \, exp\left(\sum_{j=1}^{L} \theta_j e_j^P\right) \tag{39}$$

$$\widehat{\theta_{MT}} = \underset{\theta \in \Theta}{argmax} \, \bar{e}_n(\theta) \tag{40}$$

$$\bar{\sigma}\left(\sum_n^b j, M\right) = \frac{\sum_n^b}{\sqrt{\sigma_M^2 + \left(\sum_n^b\right)_{jj}}} \tag{41}$$

Each encoder layer receives the output from the previous layer, applies the convolutional operation, and passes the result to the next layer. As the network becomes deeper, the resulting features become more complex, forming a hierarchical representation of the input data. Smooth features are characterized by gradual variation and slow change in the input data, whereas sharp features exhibit abrupt, rapid changes. All three feature types can be extracted from very similar convolutional layers with batch normalization and ReLU activation; however, the differences lie primarily in the kernel sizes of those layers. The larger kernel sizes will allow the extraction of broader spatial relationships and broader patterns of change within the data than smaller kernel sizes. The neural network will have encoder layers for both sharp and smooth features, with the encoder producing sharper feature maps at the bottom of the encoder section, while the encoder produces smoother feature maps at the upper portion of the encoder section. As a result, this type of encoding allows the network to capture both local and global features of the input data, thereby creating a fuller representation.

The decoder layers of the network will then take the encoder layer's outputs and apply the inverse of the encoder operations to recover the original input data. Convolutional layers of the decoder will generally use larger kernel sizes to upsample features and produce sharper outputs than those produced by the encoder. The technique of deep feature concatenation is often used to combine the encoder's sharp features with the sharp features. Finally, once the concatenated deep features are generated, the output will be fed into a softmax layer. The purpose of the softmax layer is to take the concatenated features and convert them from a feature vector into a set of probability scores based on the features' characteristics. Using a nonlinear transformation function, a softmax layer generates a set of probability scores from the concatenated features. By combining both sharp and smooth feature representations in this manner, a deep neural network can learn both local and global patterns within the input data. As a comprehensive representation of the dataset's overall characteristics, the network can learn to produce accurate classifications and predictions from the input dataset and is therefore a powerful model for many applications, including image classification, speech recognition, and natural language processing.

3.4. Proposed Algorithm

This process will begin by taking images from a dataset. In its raw state, those pictures will contain background noise or other unknown sources of interference that could impede the performance of our classification technique. The first stage of the algorithm is to remove background noise from the image set using a noise-removal function. The second stage includes implementing a loop function that systematically iterates over the collection of input images and builds a new array with dimensions A, B, and C, which will hold all augmented images created in subsequent steps. Next, an augmentation mask will be applied to the spatial component of the input images in a consistent, controlled manner. The following illustrates how the suggested algorithm was constructed:

Algorithm 1: Deep learning algorithm for Medical Images	
Input: Images from the dataset;	
Output: Classify the Images;	
Step 1	START
Step 2	REMOVE_Noise (n);
Step 3	Do
Step 4	for a = 1 to IMG(1)
Step 5	INITIALIZE_IMG_Array = Size [A, B, C];
Step 6	Aug.Mask = Trans (Spatial);
Step 7	IMG.mask = IMG.mask [0];
Step 8	RETURN (aug.IMG [0], mask (IMG (n)));
Step 9	End for
Step 10	PATCH_Zsize = IMG.Array [1];
Step 11	Aug.IMG = Trans.noise (n);
Step 12	END

The first step in this process is to apply a mask to the first image and store the result. The second step is to determine the size of the mask relative to the original images, since the images must be the same dimensions for the mask to work properly. The third step is to generate augmented images using the same mask that was created in step two and add them to the array of all augmented images. The array has to be resized to accommodate the newly generated augmented images, so that it does not lose any of the original (or augmented) images. The fourth step is to add noise to all the images using a transform function that adds random noise elements, ensuring they have different features. Adding these types of variations will improve the classification model's accuracy. After this process, all augmented images along with their masks will be stored in the newly created array and can be used in the classification process, thus improving result accuracy. The PATCH_Zsize value will also be stored for use throughout the classification process, signaling its completion and enabling the use of augmented images for classification.

4. Comparative Analysis

The proposed deep learning framework (DLF) was compared with several existing approaches to machine learning (MLBA), the Blockchain-Based Digital Twin Approach (BDTA), the Adversary Detection-Deactivation Method (ADDM), and the Zero Watermarking Method (ZWS). The Medical Imaging Dataset and simulated results from a Python simulator/environment were utilized for this comparison [41].

4.1. Computation of Accuracy

The proposed deep learning-based framework for analyzing medical images is created within a metaverse, where the virtual and real worlds combine to create an environment for viewing a variety of 3D representations of a patient's body/limbs. The framework's accuracy is measured by its ability to classify medical images in the training and test datasets used in conjunction with the evaluation phase of this process, i.e., the validation set. This is accomplished using metrics that compare the framework's outputs with the actual medical images, enabling refinement through additional evaluations that measure the elaboration/accuracy of the original dataset against the framework's outputs until the desired level of accuracy is achieved. The accuracy comparison between the existing and proposed models is shown in Table 2.

Table 2: Comparison of accuracy (in %)

No. of Images	MLBA	BDTA	ADDM	ZWS	DLF
100	70.93	66.14	80.35	84.75	91.54
200	72.56	67.88	81.93	86.17	92.83
300	73.04	70.22	84.13	87.43	93.84
400	74.33	71.03	85.76	89.42	94.73
500	76.44	73.32	86.90	91.89	95.10
600	77.93	75.25	89.10	93.33	96.74
700	79.74	76.98	90.25	95.05	97.11

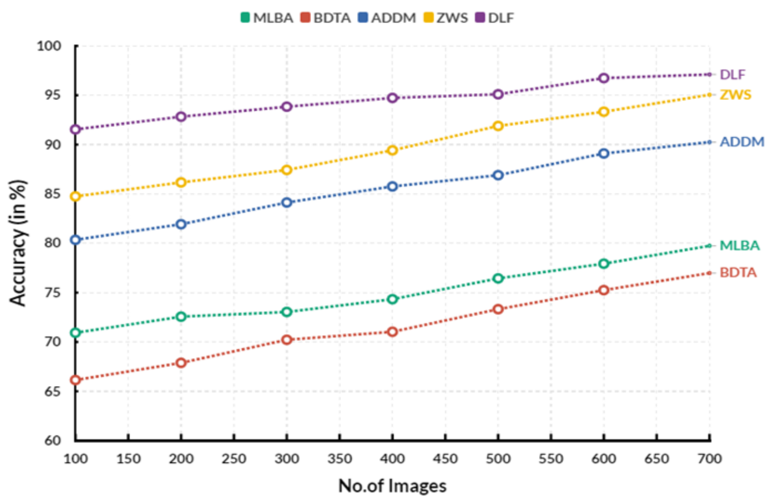

Figure 7: Comparison of accuracy

The comparison of the Accuracy of Machine Learning Algorithms and the DLF Framework, as shown in Figure 7, is presented here, per the machine learning framework described above. It can be seen that, in terms of accuracy, the DLF Framework of Deep Learning achieved 97% accuracy during training on a large medical image dataset. The DLF Framework for Deep Learning uses Medical Image Datasets to learn from over 1,000 different types of Medical Images. Once a neural network is trained on large amounts of medical image data, it learns from these datasets to make decisions about how to identify new medical images. DLF Framework will provide an opportunity to be extremely accurate in processing and identifying medical images within the Metaverse Environment through the use of Deep Learning Models that can process complex, large datasets and continue to Learn Through Repeated rounds of training iterations to Better Process and Identify Medical Images.

4.2. Computation of Precision

In medical imaging, the precision of a deep learning framework for the Metaverse can be defined in terms of the framework’s ability to correctly identify features in a given medical image(s) and subsequently classify those features as distorted or undistorted. The Metaverse deep learning framework (MDL), specifically designed for interpreting medical images, utilises a mathematical operation known as convolution to determine which features from a particular training dataset should be represented as “learned” parameters, and through back-propagation, will result in the adjustment of the learned parameters by calculating the errors between the MDL's predicted outputs and the ground truth of those training images. Subsequently, the MDL will measure its precision on an established image dataset by comparing its output against the actual (ground truth) labels for those images, repeating and optimizing this process until the MDL achieves the highest possible precision in performing accurate medical image analysis.

Table 3: Comparison of precision (in %)

No. of Images	MLBA	BDTA	ADDM	ZWS	DLF
100	53.66	67.06	79.01	85.83	93.29
200	55.15	69.03	81.43	88.03	93.28
300	55.95	70.16	81.84	88.83	94.48
400	58.28	71.35	83.44	89.50	94.96
500	59.29	71.74	85.76	90.93	96.39
600	59.93	73.26	87.01	92.02	97.55
700	60.59	73.50	89.74	92.50	98.32

The comparison of precision between the existing (i.e., with a conventional deep learning framework for medical images) and the proposed MDL is summarised in Table 3. In Figure 8, the precision comparisons among MLBA, BDTA, ADDM, ZWS, and the proposed DLF model are shown. In the existing MLBA, the overall precision obtained in a single computation cycle was 60.59%. For BDTA, the precision was 73.50%; for ADDM, 89.74%; and for ZWS, 92.50%. The proposed DLF model achieved an extremely high precision of 98.32%.

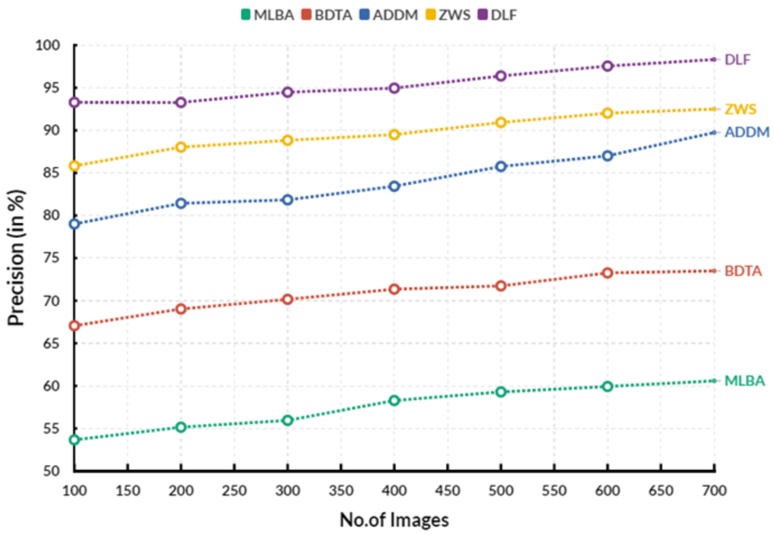

Figure 8: Comparison of precision

The high level of precision of the proposed framework was due to the use of a multi-layer neural network to extract features from input medical images. The network was trained to process the input images via convolutional layers, which learned to identify distinct patterns and features related to medical images. At that point, the convolutional layers were replaced with pooling layers, reducing the dimensionality of the extracted features and allowing the network to learn more efficiently and classify medical images more accurately. Additionally, the proposed framework utilized advanced techniques (data augmentation and transfer learning) to enhance the neural network's performance and generalization. Finally, the network learned strong, robust features from large datasets of medical images, resulting in high image processing precision.

4.3. Computation of Recall

The ability of a Deep Learning Framework for the Metaverse to recognise the many kinds of information present in a given medical image is measured by recall. When compared with ground truth or expected values for a particular medical image, recall is the percentage of relevant information an automated system correctly identifies. Based on the Deep Learning Framework's performance, higher values indicate more accurate identification of key features in the provided medical image (Table 4).

Table 4: Comparison of recall (in %)

No. of Images	MLBA	BDTA	ADDM	ZWS	DLF
100	63.55	62.96	78.85	84.82	93.29
200	65.18	64.70	80.43	86.24	94.58
300	65.66	67.04	82.63	87.50	95.59
400	66.95	67.85	84.26	89.49	96.48
500	69.06	70.14	85.40	91.96	96.85
600	70.55	72.07	87.60	93.40	97.89
700	72.36	73.80	88.75	95.12	98.66

Figure 9 displays the comparative recall values. In a calculation cycle, existing models MLBA, BDTA, ADDM, and ZWS achieved recall values of 72.36%, 73.80%, 88.75%, and 95.12%, respectively. The proposed DLF model produces a recall value of 98.66%. This framework has been created to improve the accuracy and recall of cell phone usage data in the healthcare sector using the Metaverse. Convolutional neural networks (CNNs) are deep learning models that automatically learn features from images, thereby yielding better, more reliable analyses. The high recall levels of this framework can be attributed to several factors, including large training datasets, augmented datasets generated with various augmentation techniques, and an optimized CNN architecture. Additionally, advanced techniques such as transfer learning and ensemble methods enhance recall.

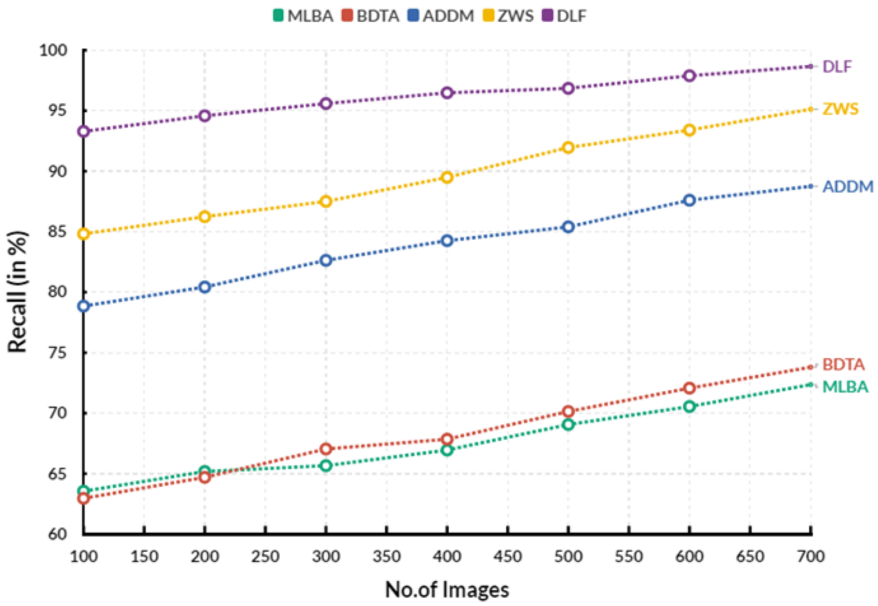

Figure 9: Comparison of recall

4.4. Computation of F1-Score

In deep learning medical imaging, the F1 score assesses how well deep learning performs. To calculate the F1 score, both precision and recall are required; therefore, it reflects the overall performance of deep learning. The precision of deep learning is defined as the ratio of true positives, or accurately anticipated positive outcomes, to the total number of positive outcomes. The ratio of real positive outcomes to all actual positive outcomes that the model should have predicted is known as recall. As a result, the F1 score generates a single numerical value that combines the two deep learning characteristics and represents overall performance. In this procedure, tagged picture data is used to train the deep learning model. An independent test data set is then used to verify the model's accuracy by calculating the F1 score of the model's anticipated results, as shown in Table 5, which compares the F1 scores of existing and proposed deep learning models.

Table 5: Comparison of F1-score (in %)

No. of Images	MLBA	BDTA	ADDM	ZWS	DLF
100	62.29	70.70	86.41	83.26	92.55
200	62.62	72.20	87.00	85.13	93.59
300	63.96	73.31	87.98	85.96	93.72

400	65.10	73.69	89.19	86.87	94.68
500	66.15	74.70	90.33	87.79	94.25
600	66.86	75.63	91.44	89.12	95.49
700	68.16	76.63	92.14	89.99	95.60

Figure 10 compares the F1-scores of different algorithms. In one run, the F1-scores yielded by the existing Multi-Layered Bayesian Algorithm (MLBA) were 68.16%, the Bacterial Foraging Optimisation Algorithm (BDTA) was 76.63%, the Active Discriminative Deep Model (ADDM) was 92.14%, and the Zero-Waterfall Scheme (ZWS) was 89.99%. However, our proposed Deep Learning Framework (DLF) yielded an f1-score of 95.60%. CNNs are often used to develop representations, or "features," of images that can be used to classify them. Therefore, the various Neural Networks utilized to create a Deep Learning Model are coupled to jointly optimize Recall and Precision and provide an F1-score that is far higher than any of the Conventional Algorithms. Furthermore, the model is trained using a wide variety of image datasets from both similar and dissimilar settings. This enables us to create a model that can identify various scenarios and generate predictions based on them. Furthermore, the use of sophisticated algorithms for optimization and Regularisation further improves the model, resulting in a higher f1-score for implementation in Medical Image Processing and adoption in the Metaverse.

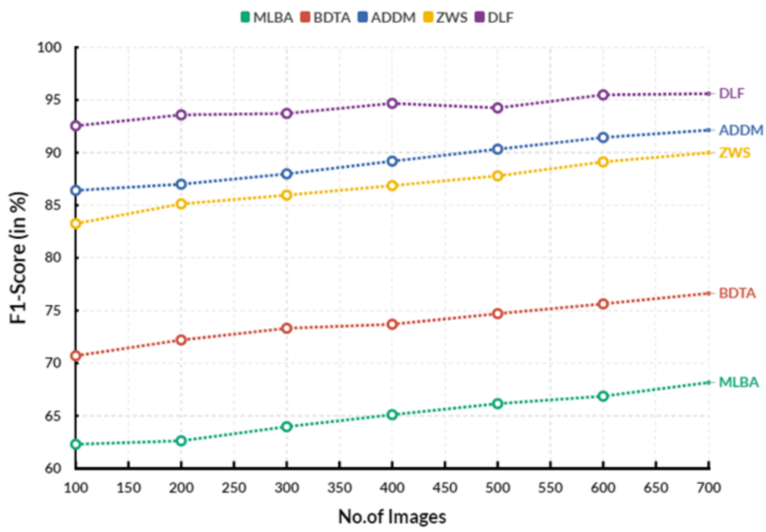

Figure 10: Comparison of accuracy

5. Conclusion

In recent years, the use of deep Learning algorithms has grown rapidly as interest in the Metaverse has increased, enabling the Medical Community to share and collaborate. AI (artificial intelligence) has great potential to address many complex problems in medical imaging, such as segmentation, classification, and image reconstruction. The Metaverse is a means of facilitating these types of interactions among professionals. The accuracy of the proposed method was measured using four distinct performance metrics: 97.11% accuracy, 98.32% precision, 98.66% recall, and 95.60% f1-score. The other critical component of the proposed Deep Learning Framework for medical imaging in the Metaverse is a decentralized data storage system that provides secure, efficient access to large volumes of medical image data stored in the Metaverse. These features create an opportunity for enhanced coordination and knowledge sharing among medical professionals, while also improving the precision and effectiveness of medical imaging analysis in a virtual setting using virtual training data, thereby removing the need for large volumes of real-world data when creating deep learning algorithms. To ensure that deep learning frameworks can effectively analyze medical data in metaverse images, healthcare providers will have to put appropriate safeguards in place to protect the privacy and security of patient information and mitigate the risks associated with these technologies.

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