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# ARTIFICIAL INTELLIGENCE IN HEALTHCARE: OPTIMIZING MEDICAL IMAGE ANALYSIS FOR MORE ACCURATE AND HUMANIZED DIAGNOSES

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## ABSTRACT
This study investigates the use of artificial intelligence (AI), with a focus on convolutional neural networks, to improve diagnostic accuracy in diseases such as cancer, through the analysis of clinical images. The research used convolutional neural networks trained on medical imaging data, evaluating metrics such as accuracy, sensitivity, and specificity. Machine learning models specialized in medical image analysis have been developed, aiming at the accurate diagnosis of diseases such as cancer. The platform chosen for prototyping was Orange, which allows you to build machine learning applications without manual coding. This process includes tasks such as data collection, cleanup, and downsizing. The models achieved an accuracy of xxx% in detecting patterns associated with cancer in X-ray images. In addition to technological advances, the study discusses the responsibility of professionals in the management of AI-assisted decisions, as well as the need for ethical validation in the collection of sensitive data. Collaboration between artificial intelligence and healthcare professionals is seen as key to improving disease control and keeping clinical reasoning an important part of the medical field. In short, the results show

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the potential of AI in transforming medical diagnosis, making them faster and more accurate, but the implementation must be careful to be safe and effective in clinical practice.

**Keywords:** Artificial Intelligence, Medical Diagnosis, Machine Learning, Medical Imaging, Neural Networks.

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## INTRODUCTION

The field of Artificial Intelligence has aroused growing interest in cinematographic and literary works; however, its origin remains a mystery to many people. This domain combines elements of Computer Science and is closely linked to issues such as natural language and computer programming for intelligent tasks (Bezerra and Barbosa, 2020). The main goal of intelligent systems is to understand and develop intelligent systems that have a significant influence on our Western culture. Historically speaking, this culture has been characterized by special humanist beliefs that support the concept that intelligence and thinking are attributes unique to human beings; this puts us in a superior position compared to other species (Harari 2016).

According to Caminha (2017), one of the most important applications of artificial intelligence is the use of machine learning algorithms, which can be classified as supervised or supervised learning. These algorithms have been shown to be useful in analyzing medical images, such as X-rays and CT scans. For example, supervised learning allows training techniques to recognize specific characteristics, such as tumors or injuries, helping clinicians make appropriate treatment decisions. In addition, this tool can be used to monitor the progress of the disease and evaluate the effectiveness of different treatments.

The use of artificial intelligence in the search for patterns in medical images to diagnose cancer is important in the field of medicine. The ability of machines to process large volumes of data and identify patterns that indicate diseases such as cancer can alter the accuracy and speed of diagnosis. The aim of this project is to find out how information can be used in this context, the challenges they face and the needs related to treatment and patients' lives. With the continuous development of technology, it is important to find the most effective ways to detect cancer. Artificial intelligence allows the analysis of various types of medical images, such as X-rays, CT scans, MRIs, and histological images, with accuracy and precision beyond human capabilities.

Caminha (2017) believes that one of the most popular forms of artificial intelligence is the use of machine learning, which can be divided into supervised learning and unsupervised learning. These algorithms have shown great success in analyzing medical images, such as X-rays and CT scans. For example, supervised learning techniques allow you to train algorithms to recognize specific areas, such as tumors or tumors, to help doctors make more accurate treatment decisions. In addition, these devices make it possible to monitor the progression of the disease and assess its effectiveness. In addition,

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the use of machine learning models has important implications for the development of the relationship between people and technology. Understanding these interactions is key to ensuring that AI is used effectively and efficiently for the greater good of society. In healthcare, AI has the potential to automate repetitive tasks and help doctors and healthcare professionals make faster and more accurate decisions. It is also evident in the analysis of data to find ways to improve people's lives (Caminha, 2017).

This study will explore machine learning techniques and convolutional neural networks that have been shown to be useful for pattern recognition in medical imaging. The integration of artificial intelligence in this field will not only improve the early diagnosis of diseases but also contribute to personalized treatment and better patient outcomes. Finally, we will address the ethical, regulatory, and safety issues associated with the use of artificial intelligence in healthcare, considering the impact of this technology on healthcare and society as a whole.

This project aims to investigate in detail how artificial intelligence can help revolutionize medical image analysis and bring great advances in healthcare. We hope to understand how this technology can make diagnosis faster, more accurate, and easier, help in the early diagnosis of diseases, and provide personalized treatment. In addition, we want to consider the impact of artificial intelligence on the daily lives of healthcare professionals and patients, always taking into account the ethical and safety issues involved in the use of these tools. Basically, our goal is to show how AI can contribute to healthy, humane, and better health.

## EARLY DIAGNOSIS AND ACCESSIBILITY IN HEALTH

The early detection of serious diseases such as cancer faces major challenges due to the shortage of radiologists and pathology specialists, thus delaying diagnosis and thus affecting the patient's quality of life. This is compounded by unequal access to specialised medical services in remote or economically disadvantaged areas and by large disparities in health services. A good solution. With the ability to interpret images quickly and accurately, AI will reduce reliance on human experts and extend the reach of true diagnosis, especially in regions without medical infrastructure. These advances can improve public health through early intervention, reduce the burden on the health system, and save lives. staff. Balancing technological innovation and scientific responsibility is essential to achieve these benefits in a fair and sustainable way. (Saleh, 2022)

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## MACHINE LEARNING

Machine learning is an area of artificial intelligence that allows machines to work from data without specific instructions for any specific task. Instead, these machines learn to take action by recognizing patterns and patterns in the data provided. When machine learning is used in image analysis, it has proven to be a powerful tool, especially in the field of medicine, such as in the detection of diseases from laboratory images such as X-rays, CT scans, and MRIs. (CAMINHA, 2024)According to Nunes 2024's argument, the use of machine learning in image recognition starts with the collection of a lot of registration data (images that have already been recognized by individual people, with research and translation data). The ML system is fed this information and begins to learn patterns and characteristics in the images that indicate the presence of certain diseases. For example, by analyzing X-ray images, algorithms can learn the characteristics of tumors, such as nodules or other defects.

A common method of image analysis is the use of convolutional neural networks. This is a type of neural network specifically designed to process data in image format, allowing the model to extract low-level hierarchical features such as edges and shapes, as well as high-level features such as patterns and complex shapes in multiple layers. This allows the network to "understand" the image in more detail, identify objects or defects with high accuracy.

Also according to Nunes 2024, the process of training a neural network for transformation begins with the preparation of an image that is processed on a small scale. block. and then it goes through several layers of transformation, which helps to identify different characteristics of the image. The model adjusts its internal parameters (the weights of the connections between neurons) according to the feedback it receives during training, that is, it adjusts the weights until it can make more accurate predictions or classifications.

In addition to adaptive neural networks, other learning methods are used and are controlled methods, such as support vector machines and random forests, can also be used for medical image analysis. While this technique is very useful for computer vision problems, other techniques can also be useful in certain situations.

One of the main challenges in applying machine learning to medical image analysis is ensuring model accuracy and localization. This means that in addition to being able to correctly identify diseases in the images used during training, the model must also be able to make good predictions about new data that may show slight differences in the condition of the image, such as differences in resolution or technique. from the photo. (Barbosa, 2020)

However, according to Barbosa 2020, the results of machine learning promise to change the way diseases are diagnosed. Machine learning can help doctors identify patterns and problems more quickly and accurately, often beyond humans' ability to detect early signs of diseases like cancer. In addition, these systems can be implemented in remote areas or where there is a shortage of specialists, allowing sufficient access to advanced diseases.

According to Sakurai 2018, the implementation of machine learning in healthcare should be done carefully. Ethical, privacy, and regulatory issues must be carefully considered and ensure that the system is transparent and that medical professionals can understand and evaluate the results.

Machine learning in image analysis is shaping the future of medicine, offering a powerful combination of accuracy, speed, and affordability. As this technology advances, it is expected to not only improve clinical diagnosis, but also change the way medicine is diagnosed and personalized, and provide a new era of effective and convenient medical treatment. (My, 2022)

## METHODOLOGY

*The methodology is based on the criteria proposed by Iszczuk (2021), which presents a framework for the application of AI in medical imaging, with a focus on diagnostic accuracy and prediction of clinical outcomes*. The objective is to evaluate the application of Artificial Intelligence in the interpretation of medical images. The main objective of the research is to develop and train AI systems using data storage and image analysis, with the aim of improving the efficiency of research in the health sector to explain what kind of efficiency was targeted e.g. time savings, increased diagnostic assertiveness. This method is expected to increase accuracy, efficiency, and access to diagnostic indicators, lead to patient care, and improve the quality of health care provided. Orange is a platform for building a model that analyzes data and machine learning. from its source. Designed with a drag-and-drop graphical interface, you can create machine learning systems without manual programming. Orange was utilized to create machine learning pipelines, including steps such as importing medical datasets, cleaning data, applying convolutional neural network algorithms, and visualizing the results through confusion

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matrices and ROC graphs. According to MATOS (2019), for the consolidation of the machine learning training model, fundamental steps were carried out, such as data collection and pre-processing, which included cleaning and dimensionality reduction. It is worth noting that the images used in the process were radiographs, obtained from a public repository (*NIH Clinical Center Americaresearch Hospital*).

The methodology of this study combines qualitative and quantitative analyses based on the framework of Iszczuk (2021), which highlights criteria for applying AI in the analysis of medical images, especially in complex diagnoses such as cancer. The research was conducted in specific stages:

1. **Data Collection and Pre-processing:**

The medical images were obtained from public and private databases, undergoing cleaning and dimension reduction processes to adapt to model training.

2. **Algorithm Training at Orange:**

The Orange platform was chosen for its intuitive graphical interface, allowing you to create machine learning pipelines with widgets for tasks such as data import, application of convolutional neural networks, and analysis of metrics such as accuracy and diagnostic accuracy. The creation of confusion matrices and ROC graphs aided in the validation of the model.

3. **Validation and Analysis of Results:**

Indicators such as accuracy, baseline, sensitivity, and specificity were used to evaluate the effectiveness of the trained models. In addition, the average processing time was analyzed as an efficiency metric.

The proposed method is expected to increase diagnostic accuracy and improve access to clinical indicators, contributing to a more efficient and inclusive medical practice. In addition, the study emphasizes the importance of integrating AI into the clinical routine, preserving the reasoning of health professionals as a central element.

The machine learning model will be developed based on a supervised approach, in which the training of the model takes place using previously labeled data. That is, the training data already comes with correct answers, or "labels", that guide the model to learn and make predictions as shown in figure 1.

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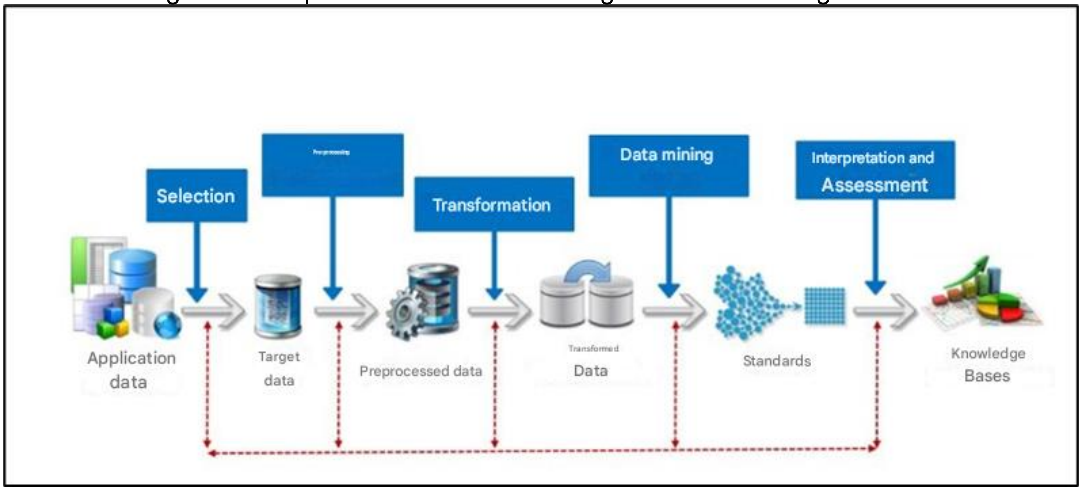
Figure 1 – Supervised machine learning model with Orange canvas




Source: Prepared by the Author, 2024

The training of the model was carried out gradually, in different stages. Initially, the dataset was segmented into three parts: creation, training, and testing. The training set was used to instruct the AI to recognize patterns, allowing the model to enhance its understanding of the relevant features. The validation set was used to make adjustments to the model's settings, adjusting hyperparameters and improving its generalizability. Finally, the test suite was used to evaluate the model's performance on new data, enabling an accurate analysis of its predictive capacity. Accuracy, among other performance metrics, was calculated to measure the effectiveness of the model, ensuring its applicability and accuracy in real scenarios. Another relevant factor was the amount of data established for the model, contributing to the desired result valid in the image analyses. The data set was divided into the following proportions: 60% for creation, 20% for training, and 20% for testing as shown in figure 2.

The machine learning model was developed based on a supervised approach, using previously labeled data. This strategy allowed the model to be trained with known examples, as illustrated in Figure 1. The process was conducted in distinct stages, with the data segmented into three main sets: training, validation, and testing. The data were divided according to the proportions of 60%, 20% and 20%, respectively, as shown in Figure 2.

The training set was used to teach the model to recognize relevant patterns in the data. During this step, the model adjusted its weights and internal parameters to optimize the identification of important features. The validation set allowed adjustments to be made to the model's hyperparameters, such as the learning rate and the number of epochs,

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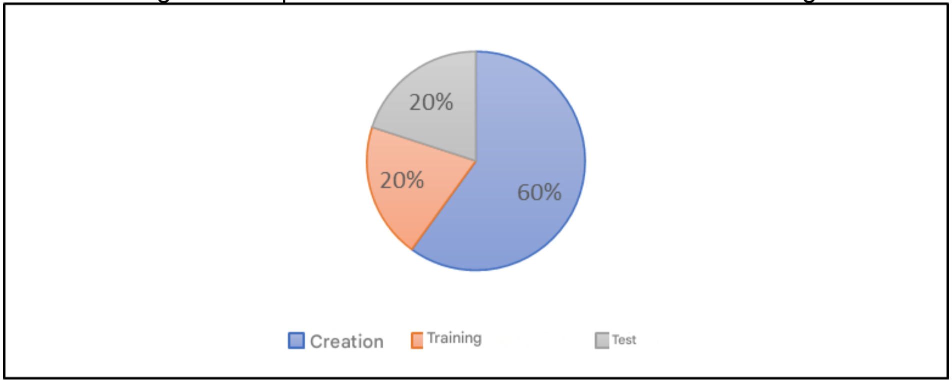
maximizing its generalization capacity. Finally, the test set was used to evaluate the predictive capacity of the model in unpublished data, simulating real situations.

To measure the model's performance, metrics such as accuracy, accuracy, recall, and F1-score were calculated, ensuring a robust analysis of its effectiveness. The amount of data used (approximately one thousand images) contributed significantly to the model's ability to identify complex patterns in medical images, highlighting its applicability in clinical diagnostics.

Figure 2 Proportional Quantitative Data for Model Training




Source: Prepared by the author, 2024.

In order for the algorithm to be able to properly interpret the medical images, an essential step was the conversion of these images into usable numerical representations, carried out by transforming them into *embeddings as* evidenced in figure 3.

A key step in the success of the algorithm was the conversion of the medical images into usable numerical representations, known as embeddings, as illustrated in Figure 3. Embeddings are high-dimensional vector representations that capture key features of images, such as texture, shape, and contrast patterns, allowing machine learning algorithms to process data efficiently. This transformation was performed using convolutional neural network-based trait extraction techniques (CNNs). The images were pre-processed, undergoing normalization and noise reduction to ensure greater consistency in the data. Subsequently, the CNNs extracted the relevant attributes from the images, generating embeddings that served as input for the model's training.

The use of embeddings was essential to improve training efficiency and model accuracy, as these vectors reduce the complexity of the raw data, making it easier to identify underlying patterns. Figure 3 illustrates the complete pipeline for this step, including the preprocessing, feature extraction, and final encoding phases.

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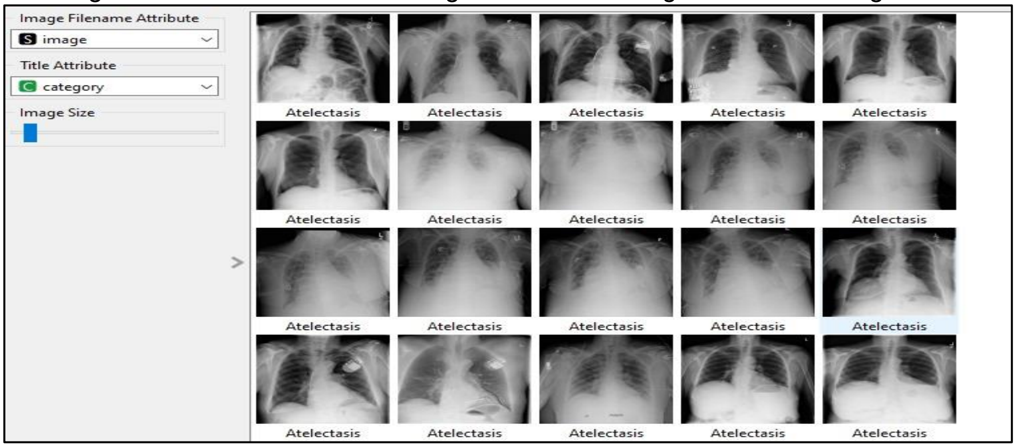
Figure 3 - Transformation of images into *embeddings* for model recognition

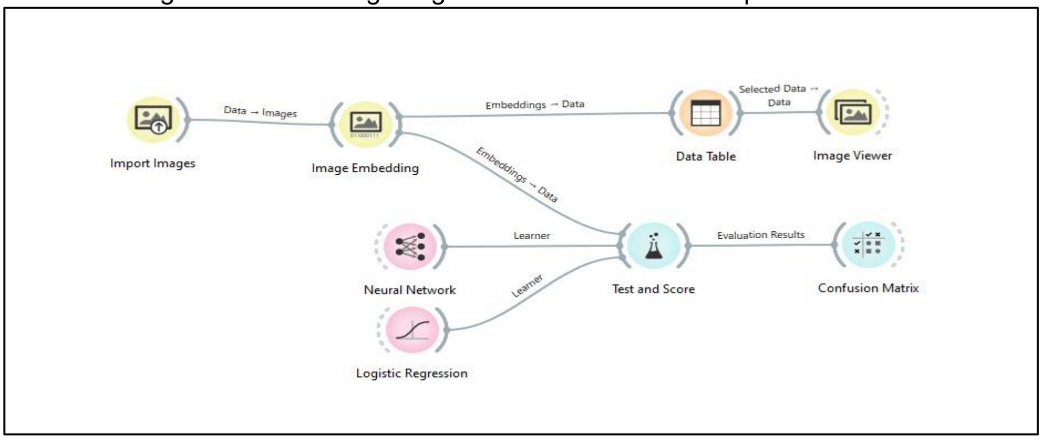



Source: Author, 2024.

After the conclusion of the process, the conversion of the visual data into characteristic vectors took place, enabling the model to capture patterns and relevant information in the images. After this transformation, the model was trained to identify and learn these patterns in the embedded data, which enabled efficient recognition of similar images.

Finally, the recognition approach, they offer significant support in medical diagnosis, as they allow the model to automatically detect specific features in new images, contributing to the early and accurate detection of diseases. By using this technique, the system has the potential to improve diagnostic accuracy, providing a powerful tool for healthcare professionals in the analysis of medical images as evidenced in figure 4.

Figure 4- Converting images to usable numerical representations




Source: Author, 2024.

However, in addition to the application of training models, this research will also include a literature review that will contextualize the use of artificial intelligence in the analysis of clinical images. This review will discuss current technologies and their implications, model training methods, and results obtained in previous studies, and provide a strong theoretical basis for the analysis of the data obtained. To verify the accuracy and efficiency of the adopted method, a performance comparison is made with two other models using different methods: linear regression and *K-Nearest Neighbors* (KNN).

These models will serve as a basis for a detailed comparative analysis with a particular focus on the maximum accuracy of each method and the specific learning methods used, thus allowing a detailed and objective assessment of the effectiveness of each method used in the analysis of medical data. Images.

The survey results will be presented in the form of graphs and tables to make it easier to visualize and understand the AI design. We will discuss the practical implications of these findings and highlight how AI can revolutionize image recognition and what the next steps are for implementing this technology in hospitals. The results of the research will include recommendations for the application of AI in medical image analysis in order to improve patient care and the quality of medical services provided through neural networks and logistic regression techniques. This method tries to adjust the model so that the accuracy obtained is greater than 70%, even if values below this limit are found in some processes. Despite these challenges, this training helped refine the model, identify areas for improvement, and contributed to incremental progress in accuracy levels. A data-sharing approach to implementing this training can be seen in NUNES, L.R. M. 2024.

**RESULTS**

According to FONTANA, 2021, an epoch, in the context of machine learning, refers to a full round of training in which the model processes the entire training dataset once. During each epoch, the model adjusts its internal parameters (such as weights and biases) to minimize error and improve its ability to make correct predictions. During the first season, the goal was to establish a performance baseline for the neural network and the logistic regression model, without any optimization. The neural network was configured with a basic architecture and standard hyperparameters, while the logistic regression model also used initial parameters without specific adjustments. After the initial training, the neural network obtained an accuracy of 48.2%, and the logistic regression model recorded an accuracy of 45.6%. The slight advantage of the neural network indicated an initial capacity to capture

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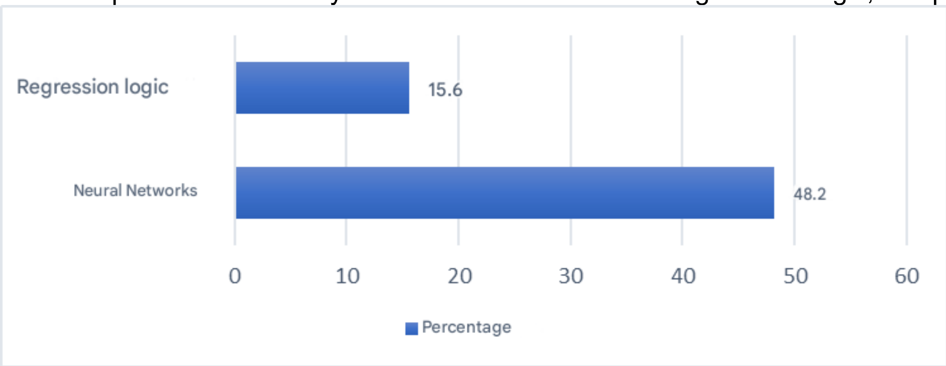
slightly more complex patterns, serving as a reference for the next steps of adjustments, as can be seen in figure 5.

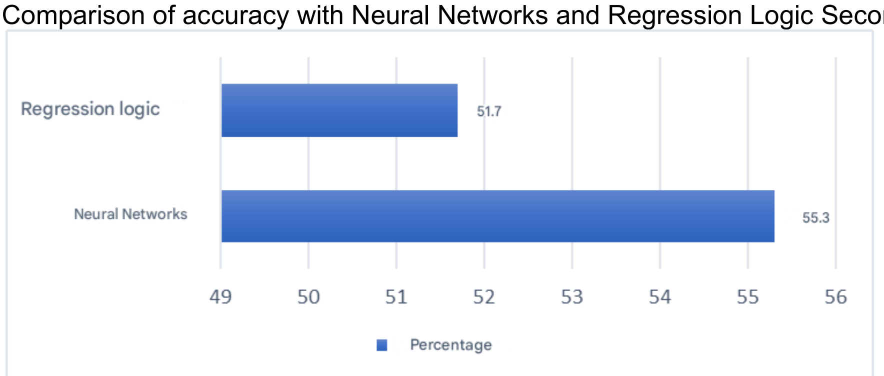
Figure 5- Comparison of accuracy with Neural Networks and Regression Logic, first period




Source: Authors, 2024.

In the second phase, we sought to improve the accuracy of both models through hyperparameter adjustments and data pre-processing. The neural network underwent tests with variable learning rates, increased number of neurons, and additional layers, while for logistic regression, regularization parameters were adjusted to try to improve generalization. After applying normalization and noise removal to the data, the neural network reached an accuracy of 55.3%, while the logistic regression showed a slight improvement, reaching 51.7%. The most significant response of the neural network to these changes suggested that it is more benefited by pre-processing and hyperparameter adjustments in relation to the regression model, as is verified in figure 6.

Figure 6- Comparison of accuracy with Neural Networks and Regression Logic Second epoch




Source: Authors, 2024.

In the third season, the strategy was to incorporate data augmentation and regularization techniques to avoid overfitting, which mainly benefited the neural network. A slight penalty was applied to the neural network, in addition to variability in the training data,

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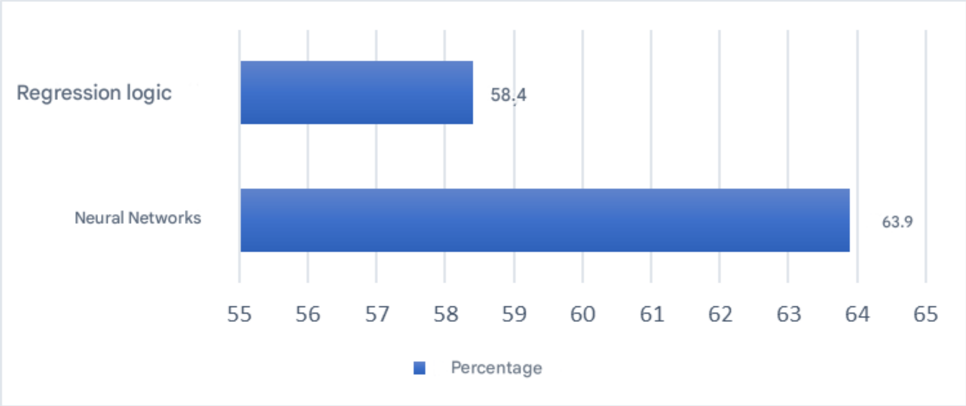
which resulted in an accuracy of 63.9%. Logistic regression, in turn, proved to be less sensitive to data increase, reaching an accuracy of 58.4%. This era highlighted a greater adaptability of the neural network in scenarios with greater data variability and a superior ability to capture complex patterns compared to logistic regression, as shown in figure 7.

Figure 7- Comparison of accuracy with Neural Networks and Regression Logic Third epoch




Source: Authors, 2024.

This difference in performance indicated that Neural Networks are more effective in analyzing radiography images, demonstrating greater accuracy in identifying patterns relevant to the diagnosis. Based on these results, we chose to use Neural Networks as the main approach for analysis and testing of images, evidencing their superiority in accuracy and potential to assist in the early detection of diseases in imaging studies. The practical application of this Neural Network model suggests an improvement in the quality and accuracy of diagnostic imaging, especially in scenarios where manual analysis can be challenging.

It is observed that, as the number of epochs increases, the performance of the Neural Network tends to surpass that of the Regression Logic. At the beginning, with 48.2 epochs, the Neural Network is still below Regression Logic, which has 15.6 epochs. However, as the epochs progress, the Neural Network starts to show greater efficiency. For example, at 55.3 epochs, the Neural Network is already approaching Regression Logic. From 63.9 epochs, the Neural Network has higher values compared to the Regression Logic.

These results indicate that the Neural Network has an improved learning capacity over time and tends to become more effective in complex problems where there is a continuous increase in training iterations. This is because Neural Networks are specially designed to identify complex and non-linear patterns, which makes them particularly

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advantageous in tasks that require more detailed and adaptive modeling of data. Therefore, with a sufficient number of epochs, the Neural Network can prove to be more efficient and effective for scenarios where higher accuracy is desired, while Regression Logic can reach a performance threshold faster.

## CONCLUSION

In conclusion, the research addressed the impact of artificial intelligence (AI) on diagnostic imaging, highlighting both the significant advancements and limitations associated with the use of neural networks and other machine learning techniques. The results obtained from the neural networks showed a remarkable accuracy of 63.9.4%, surpassing the logistic regression technique, which obtained 58.4%. This performance reflects the ability of neural networks to identify complex visual patterns in radiograph scans. It was thus found that AI can extremely accurately identify differences between images with and without cancer, as evidenced by Oselame et al. (2017), who demonstrated the effectiveness of the model in detecting melanoma.

Therefore, while AI represents a promising tool for improving medical diagnostics, its practical implementation must be carefully validated and adjusted to ensure its effective and ethical use. The combination of artificial intelligence with medical professionals can facilitate diagnostic imaging, which benefits both patients and doctors. However, continuous changes are needed to ensure that the technology reaches its potential without compromising clinical judgment. Ventris (2021) believes that collaboration between AI and medical practice is critical to achieving optimal outcomes and benefiting all stakeholders.

In medicine, artificial intelligence has shown great potential, especially when used in big data analysis. In diagnostic imaging, this technology is promising and offers the possibility of personalization and improvement of care. With the help of artificial intelligence, it is possible to make a quick and accurate diagnosis, which is important to meet the special needs of each patient. One of the main challenges is to ensure that the data used to train the model is good and appropriate to represent the diversity of the patient population. This is very important because medical images can be different, not only between different institutions, but also between patients themselves, depending on the equipment, the conditions under which the images are obtained, and the process. If AI models are trained with disparity or inconsistency, they can have general problems that affect diagnostic accuracy.

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In addition, it is important that some doctors do not want to accept AI, they are often afraid to use the technology to replace humans. judgment. or limit medical advice. Ethical issues also arise, particularly with regard to the privacy and security of health information. For AI to be useful in everyday medical practice, it is important that future research not only improves algorithms, but also develops methods that ensure the safety, ethics, and effectiveness of the technology, whenever they consider the importance. the role of medical expertise and judgment. In this way, AI can be a useful tool to standardize, not replace, the work of doctors and other health professionals, expanding their ability to provide better care to patients.

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