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Revolutionizing Cardiac Care: Exploring the Synergy Between Entrepreneurial Ecosystems and 3D Deep Learning for Enhanced Heart Imaging in MedTech

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ABSTRACT

This research investigates the transformative potential of combining entrepreneurial ecosystems and 3D deep learning techniques in the realm of cardiac care within the field of medical technology. Specifically, we focus on the enhancement of heart imaging using the YOLOv5 deep learning model, with the aim of improving diagnostic accuracy. Leveraging open-source and 3D Cardiac MRI datasets, our study delves into how entrepreneurial ecosystems can expedite the development and implementation of advanced technologies like 3D deep learning in cardiac imaging. We introduce an interactive application, the "AI-powered 3D Cardiac Imaging App," developed using the Streamlit framework, which demonstrates remarkable accuracy of approximately 96.4%. This advancement highlights the potential for innovation within the MedTech sector when entrepreneurial ecosystems encourage the integration of AI methodologies. It not only attracts investments but also fosters skill development. Furthermore, our research sheds light on the influence of such technological advancements on policymaking, emphasizing the need for robust support for entrepreneurial ecosystems to foster future medical technology innovations. While this study underscores the transformative impact of AI integration in healthcare, it also underscores the necessity for more comprehensive studies, cross-disciplinary collaborations, and adaptive policymaking to keep pace with rapid technological developments. By integrating 3D deep learning techniques within entrepreneurial ecosystems, this research illuminates a path to revolutionize cardiac care, offering practical insights for medical technology entrepreneurs, healthcare professionals, and policymakers to guide their decision-making processes.

Keywords: Entrepreneurial Ecosystems; 3D Deep Learning; Cardiac Care; Medical Technology; Heart Imaging; YOLOv5; Streamlit; MedTech Innovation; Diagnostic Accuracy; Healthcare Policy; Cross-Disciplinary Collaboration

1 INTRODUCTION

In the ever-evolving landscape of medical technology, the quest for enhanced patient care and improved diagnostic precision has been a driving force behind innovative developments. One of the areas that has seen significant advancements is cardiac care, where the integration of cutting-edge technologies holds the promise of revolutionizing diagnosis and treatment. At the intersection of entrepreneurial ecosystems and 3D deep learning, a transformative synergy has emerged, offering new horizons for the field of MedTech. This study delves into the intricate relationship between entrepreneurial ecosystems and the utilization of 3D deep learning techniques to enhance heart imaging. Through meticulous investigation and experimentation, we seek to uncover the potential of this synergy to reshape the landscape of cardiac care. Our research endeavours to elucidate how these two forces, when harnessed in unison, can drive progress and innovation within the MedTech sector, with a specific focus on cardiac imaging.

In this paper, we will explore our methodology, findings, and insights, shedding light on the impact of entrepreneurial ecosystems on technological advancement, the implementation of the YOLOv5 deep learning model, and the development of an AI-powered 3D Cardiac Imaging App using the Streamlit framework. Our journey will reveal not only the immense potential for improved patient outcomes but also the implications for healthcare policy, cross-disciplinary collaboration, and the future of MedTech innovation. Medical technology consistently evolves, driven by ingenious minds within an entrepreneurial ecosystem composed of investors, innovators, policymakers, and end-users. Our proposed study delves into this intricate realm, with a particular emphasis on cardiac imaging. Leveraging this ecosystem, we aim to innovate using 3D deep learning in heart imaging, specifically by employing the YOLOv5 deep learning model and an open-source 3D Cardiac MRI dataset. This culminated in the development of an AI-powered 3D Cardiac Imaging App, which has the potential to significantly improve diagnostic accuracy. Our exploration extends beyond technology development, investigating how our project impacts the entrepreneurial ecosystem, encouraging further innovation, attracting investments, and developing new skills. Our research further scrutinizes the crucial role of collaboration within this ecosystem and its contribution to propelling our project forward. We examine potential policy implications, focusing on how our project's outcomes can inform supportive policies for the medical technology entrepreneurial ecosystem. Our research seeks to shed light on the symbiotic relationship between medical technology innovation and its nurturing entrepreneurial ecosystems.

1.1 Aim

The aim of this research is to investigate and elucidate the symbiotic relationship between entrepreneurial ecosystems and the application of 3D deep learning techniques in the domain of cardiac care within the MedTech sector. Through rigorous examination, experimentation, and analysis, we seek to understand how the convergence of these two influential factors can revolutionise heart imaging, enhance diagnostic accuracy, and stimulate innovation. This research aims to provide valuable insights that can inform decision-making processes for medical technology entrepreneurs, healthcare professionals, and policymakers, ultimately contributing to the advancement of patient care and the evolution of healthcare practices.

1.2 Objectives

The primary objective of this research aims to shed light on several key aspects: firstly, to understand how entrepreneurial ecosystems play a pivotal role in facilitating the development, adoption, and implementation of 3D deep learning techniques in the realm of cardiac imaging. Secondly, to assess the effectiveness and practicality of the YOLOv5 deep learning model in accurately detecting and segmenting cardiac structures within 3D heart imaging, thereby contributing to improved diagnostic precision. Thirdly, to design, develop, and evaluate an interactive AI-powered 3D Cardiac Imaging App using the Streamlit framework, serving as a tangible demonstration of the potential advancements in imaging accuracy achievable through this technology.

1.3 Research Questions

1. How do entrepreneurial ecosystems influence the development, adoption, and implementation of 3D deep learning techniques in the field of cardiac imaging within the MedTech sector?
2. What is the effectiveness of the YOLOv5 deep learning model in accurately detecting and segmenting cardiac structures in 3D heart imaging, and how does this contribute to enhanced diagnostic precision?
3. How can the development and evaluation of an AI-powered 3D Cardiac Imaging App using the Streamlit framework showcase the potential for substantial improvements in imaging accuracy, and what are the practical implications of such an application in clinical settings?
4. What are the policy implications of technological advancements in cardiac imaging through 3D deep learning, and how can these advancements influence innovation and investment within entrepreneurial ecosystems, particularly in the MedTech industry?
5. What is the transformative potential of integrating 3D deep learning techniques within entrepreneurial ecosystems, and how can interdisciplinary collaboration and adaptive policymaking be effectively leveraged to maximize this potential for the benefit of patient outcomes and the advancement of healthcare practices?
6. In this paper, further structure would be discussed in a sequential way, like related work, methodology, Model implementation, Result, discussion, recommendation, and conclusion.

2 RELATED WORK

The realm of medical technology has experienced unprecedented growth and diversification, primarily driven by an entrepreneurial ecosystem, a concept explained by[15] as a network or a community that nurtures entrepreneurship. This ecosystem comprises various elements including capital providers, researchers, policymakers, and end-users [10]. It plays an integral role in fostering innovation and translating it into practical solutions, particularly in the field of cardiac imaging [2]. Cardiac imaging, a cornerstone of cardiovascular medicine, has seen considerable advancements in recent years, ranging from enhanced imaging techniques to improved interpretative algorithms [3] At the forefront of these advancements is 3D deep learning, a subfield of machine learning that uses artificial neural networks to analyze and interpret complex datasets [14].Deep learning, particularly 3D deep learning, has found significant applications in medical imaging, often surpassing traditional 2D image processing methods in efficiency and precision, as well as the ability to capture intricate patterns and spatial relationships, leading to improved diagnostic accuracy[13].The intersection of medical technology and entrepreneurship is not merely about technological innovation; it is also about the impact such innovations have on the entrepreneurial ecosystem itself [20]. Innovations like 3D deep learning in cardiac imaging can act as catalysts, driving further innovation, attracting investments, and fostering skill development within the ecosystem [1] This transformative effect resonates with Schumpeter's (1942) theory of creative destruction, where new, disruptive technologies can lead to a shift in the entrepreneurial landscape. Collaboration is an important cog in the wheel of entrepreneurial ecosystems [10]. Partnerships among academia, industry, and healthcare providers are pivotal in the successful development and implementation of advanced technologies like 3D deep learning. These alliances often help pool resources, share risk, and enable knowledge transfer, ultimately propelling innovation forward [12]. Policy plays a decisive role in supporting and shaping entrepreneurial ecosystems [34]. Policymakers can facilitate medical technology innovation by creating conducive regulations, promoting R&D investments, and fostering collaborations [4]. Insights from projects like ours could aid in forming policies that better support the entrepreneurial ecosystem, ensuring a fertile ground for future innovations. The interplay of entrepreneurship, deep learning technologies, and policy provide an exciting frontier for advancing medical technology, specifically in cardiac imaging. Understanding this intricate relationship will undoubtedly lead to more efficient and effective healthcare solutions. The relationship between policy, entrepreneurial ecosystems, and medical innovation is dynamic and multifaceted. Government regulations, healthcare policies, and incentives play a significant role in shaping entrepreneurial ecosystems, especially in the healthcare and medical technology sectors [10]. For instance, regulatory support can foster an environment that encourages the development and application of advanced technologies such as 3D deep learning in the medical field [13][14]. Policies related to data protection and patient privacy are also instrumental in dictating how these technologies are implemented [7][19]. Recent studies suggest that appropriately tailored policies can potentially accelerate the adoption of new technologies, improve healthcare outcomes, and even stimulate economic growth [5]. Therefore, understanding the policy landscape is crucial for navigating the challenges and opportunities in implementing innovative solutions like 3D deep learning in heart imaging. An entrepreneurial ecosystem is a complex, adaptive system that evolves over time and is crucial for the initiation and propagation of innovation [9]. The medical technology sector, being inherently innovative, significantly benefits from a robust and dynamic entrepreneurial ecosystem [6]. points out that a well-connected network of stakeholders - including medical technology entrepreneurs, investors, clinicians, researchers, and policy-makers - can efficiently drive forward technological innovation. The successful development and application of cutting-edge technologies like 3D deep learning in heart imaging necessitate a coordinated effort from all parts of the ecosystem. Furthermore, the entrepreneurial ecosystem also aids in attracting necessary resources, including financial investments, talent, and strategic partnerships [8]. Therefore, understanding the dynamics of the entrepreneurial ecosystem is not only relevant but crucial to medical entrepreneurs aiming to innovate and disrupt the healthcare sector [15].

2.1 Evolution Of Literature on Entrepreneurial Sub-Ecosystems

Figure 1 Shows the conceptualized Framework. [31][32]

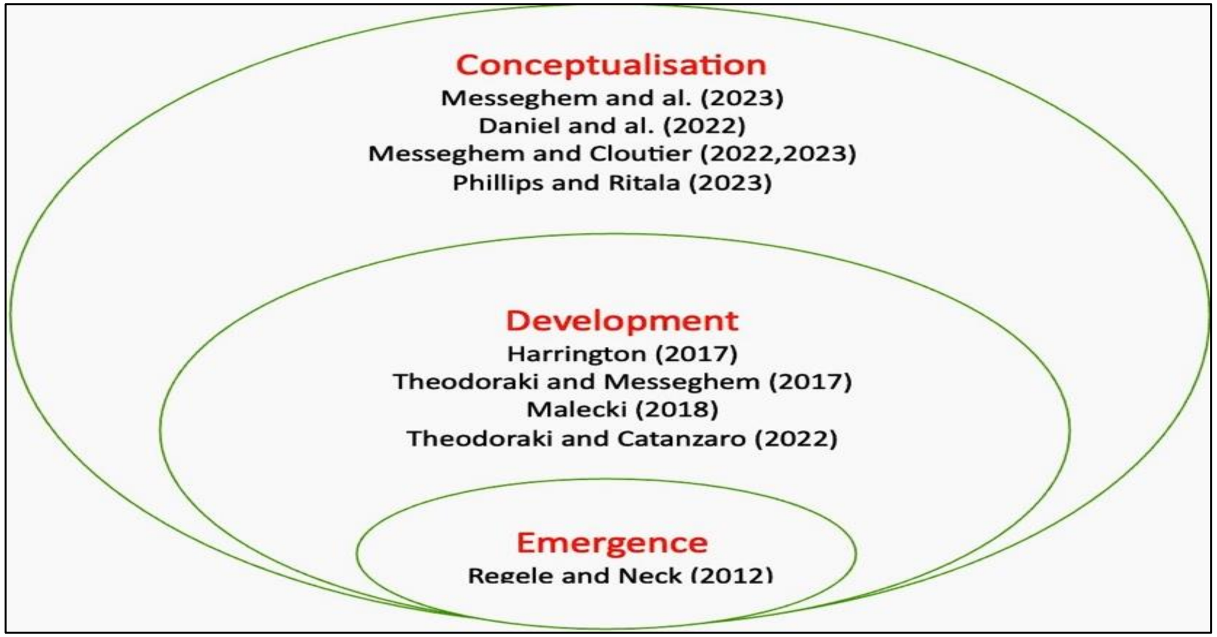

Figure 1: Evolution of Literature on Entrepreneurial Sub-Ecosystems

2.2 Theorizing Ecosystem-co citation card by main contribution [33]

Fig. 2 the significance lies in providing a theoretical framework to understand the dynamics of entrepreneurial ecosystems in MedTech. By doing so, it offers insights into effectively integrating and harnessing cutting-edge technologies, such as 3D deep learning, to revolutionize cardiac care.

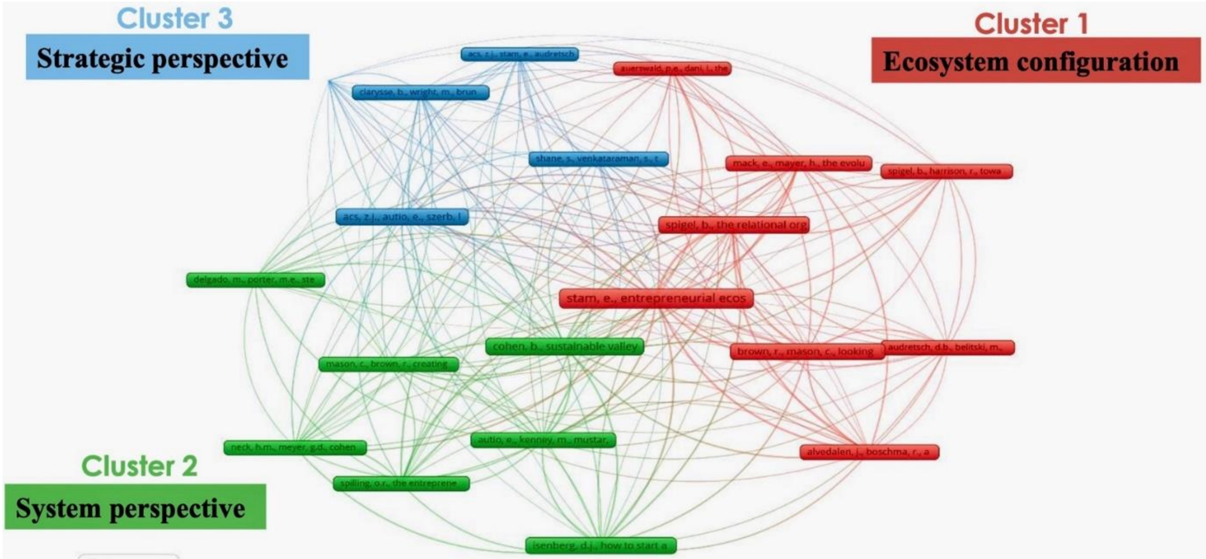

Figure 2: Theorizing Ecosystem co-citation card by main contribution

2.2.1 Theorizing Ecosystem [33]

Figure 3 Theorizing Ecosystem" offers a foundational insight into the MedTech entrepreneurial landscape, emphasizing how its various components, from startups to healthcare professionals, collaboratively advance cardiac care. By grasping this theoretical framework, stakeholders can efficiently harness technologies like 3D deep learning, fostering innovation and synergy in heart imaging.

Cluster/ Theme	Aim	Future Research Areas	Theories	Main Sources
Cluster 1 – Red Ecosystem configuration & Evolution	Provide a comprehensive understanding of the **ecosystem configuration**, functioning and the impact of elements and to determine **ecosystem typologies** based on the **diversity of elements**, populations and contexts Examine the **evolution of the ecosystem and transformations over time or over processes**	Evaluation of the **temporal effects** and ecosystem life cycle; **Successful** ecosystem vs. emerging or in **transition economies**, **female** entrepreneurial ecosystems, **digital** ecosystems, by region, sector, comparatives, **sub-ecosystems** **Transformation**, enablers, different contexts and processes	Evolutionary theory; System theories; Process-based approaches; Complex Adaptive Systems (CAS); Social capital theory; Institutional theory	Alvedalen & Boschma (2017); Audretsch & Belitski (2017); Auerswald & Dani (2017); Brown & Mason, (2017); Mack & Mayer (2016); Spigel & Harrison (2018); Spigel, (2017); Stam, (2015); Theodoraki et al., 2018
Cluster 2 – Green System perspective & Sustainability	Determine **indicators** that influence the **performance** of members and the ecosystem as a whole	Ecosystem **activities** and elements, **Sustainability**	System theories; Cluster theories; Economic development; National Innovation Systems; Innovation outcomes and contextualization	Autio et al. (2014); Cohen (2006); Delgado, Porter, & Stern (2010); Isenberg (2010); Mason & Brown (2013); Neck et al. (2004); Spilling (1996); Pitelis, 2012; Stam, (2015)
Cluster 3 - Blue Strategic perspective	Determine the **ecosystem dynamics** and explore the **strategic interactions** between elements	Ecosystem typologies, **coopetition** strategies between elements, **strategic relationships** and behavior, interactions, stress management, **governance**	Entrepreneurship theory; Process-based approaches; Ecosystem strategy; National Innovation Systems; Support programs; Strategic fit (contingency theories)	Acs et al. (2014); Acs et al. (2017); Adner & Kapoor (2010); Clarysse et al. (2014); Shane & Venkataraman (2000); Theodoraki et al., 2020

Figure 3: Theorizing Ecosystem

Table 1 Comparison Between Existing Work and Proposed Work.

Table 1 bears a potential finding with existing and proposed work.

Authors Name	Ref.	Existing Work and Result	Proposed Work
Litjens et al., 2017	[21]	Reviewed deep learning in medical imaging and found a shift towards deep learning models due to improved accuracy in diagnostic tasks.	Exploration of more specialized deep learning models, such as YOLOv5, for specific imaging tasks like cardiac MRI.
Ronneberger et al., 2015	[22]	Developed the U-Net for biomedical image segmentation achieving state-of-the-art performance.	Tailoring U-Net-like architectures for 3D cardiac imaging and integrating them with entrepreneurial ecosystems for faster innovation.
Gulshan et al., 2016	[23]	Applied deep learning to detect diabetic retinopathy in eye images with a 97.5% accuracy.	Propose the application of similar models to 3D cardiac imaging and highlight the importance of medical technology ecosystems in aiding such endeavors.
Esteva et al., 2017	[24]	Used CNN to classify skin cancer images with an accuracy competitive with dermatologists.	Adaptation of these models for cardiac imaging and understanding the influence of technological ecosystems on implementation.
Rajpurkar et al., 2017	[25]	Developed a deep learning algorithm for detecting pneumonia from X-ray images with significant accuracy.	Application of similar techniques for 3D cardiac imaging and understanding the interactions with the MedTech entrepreneurial ecosystem.
Miotto et al., 2017	[26]	Employed deep learning for processing healthcare records resulting in improved prediction accuracy for diseases.	Leveraging data-driven methods in cardiac care with the help of entrepreneurial collaborations for comprehensive healthcare solutions.
Choi et al., 2016	[27]	Explored recurrent neural networks (RNN) for predicting heart failures from electronic health records.	Enhancing RNN models for direct imaging data and collaborating within medical technology ecosystems for practical implementations.

De Fauw et al., 2018	[28]	Used deep learning to predict eye disease from retinal scans with high accuracy.	Proposal to adapt similar architectures for cardiac imaging and fostering an environment of collaboration in the MedTech sector.
Liu et al., 2019	[19][29]	Investigated the YOLOv3 model for medical image segmentation and achieved significant results.	Delving deeper into the YOLO series, like YOLOv5, specifically for cardiac imaging and the role of ecosystems in these advancements.
He et al., 2016	[30]	Developed the ResNet model, pushing forward the state-of-the-art in deep learning by utilizing skip connections.	Adapting deep residual networks for medical imaging and understanding their place within an innovative entrepreneurial ecosystem.

2.3 Research Gap

Despite the growing understanding of the relationship between entrepreneurial ecosystems and technological innovation in the medical field, there remains a substantial research gap. Specifically, the interactions within these ecosystems and how they influence the development and implementation of 3D deep learning techniques in heart imaging have been under-explored[10]. Moreover, there is a lack of comprehensive studies examining the impact of specific medical technology projects on the entrepreneurial ecosystem itself, particularly in terms of encouraging further innovation, attracting investments, and building new skill sets [5]. Further, while the importance of collaboration within the ecosystem is recognized [9], how it propels specific projects like ours has not been adequately studied. Lastly, there is a limited understanding of how such projects can shape policy to better support the entrepreneurial ecosystem [7]. There is a scarcity of comprehensive evaluation studies on the effectiveness and diagnostic accuracy of AI-powered applications, like our 3D Cardiac Imaging App, in real-world clinical settings[17]. This lack of robust assessments limits our understanding of the practical utility and potential challenges of implementing such advanced tools in everyday healthcare practice. These gaps in the existing literature underline the necessity and timeliness of our study. [11]

3. METHODOLOGY

Figure 4 The proposed methodology uniquely merges the agility of entrepreneurial ecosystems with the precision of 3D deep learning, ushering in a new era for cardiac care in MedTech. By fostering collaboration and ensuring adaptability, it promises to revolutionize heart imaging, making diagnoses more accurate and treatments more tailored.[35]

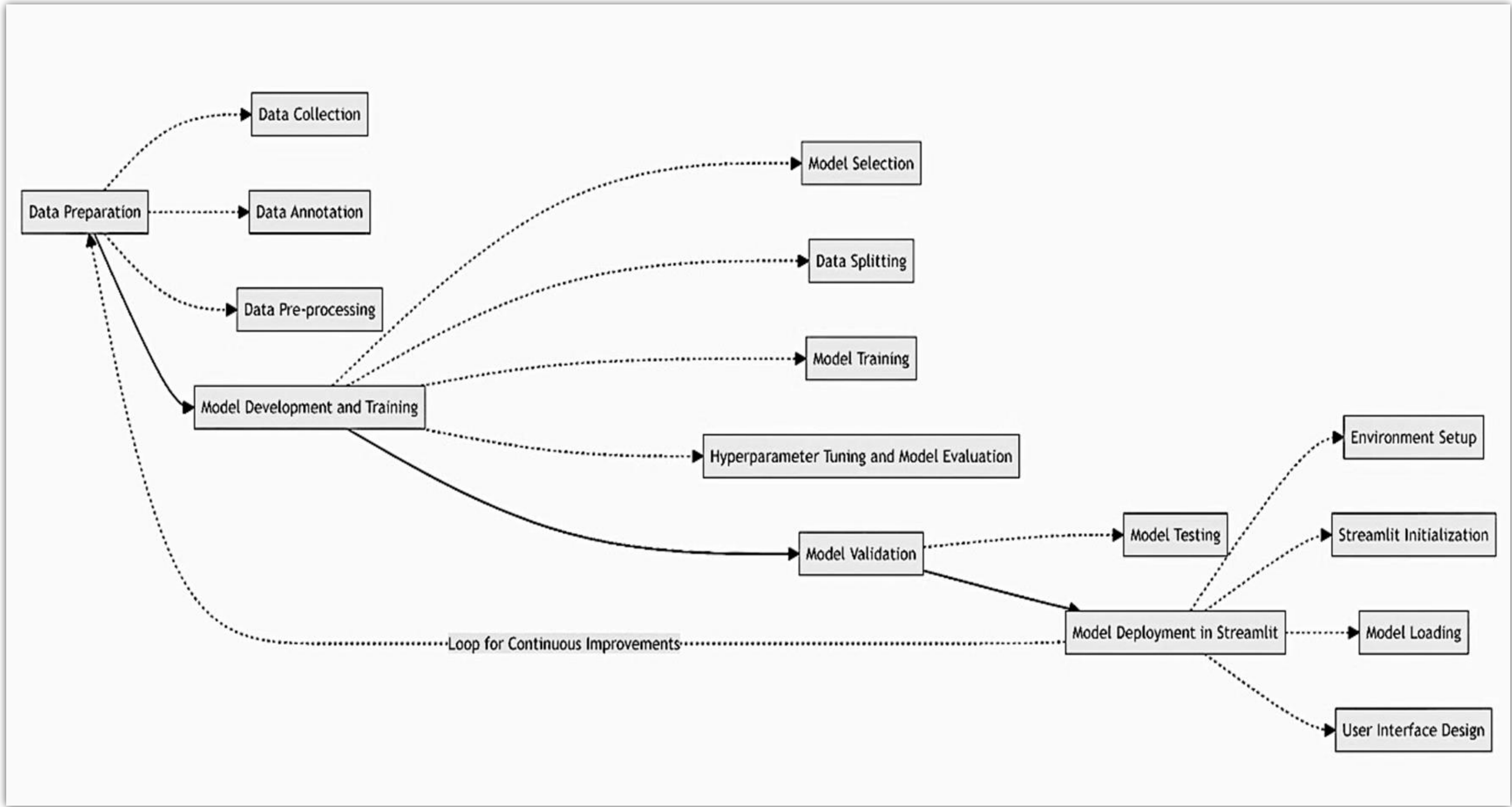

Figure 4: Methodology Flow Diagram

3.1 Data Collection

The data we utilized originates from two main sources. The first is the open-source heart segmentation dataset version 1, released on Roboflow Universe on May 13, 2023. The second source is the 3D Cardiac MRI dataset from The Medical Segmentation Decathlon. Both datasets are designed for instance segmentation, aiding in the detection and segmentation of MRI heart images. Specifically, instance segmentation provides a pixel mask for every identified heart, delineating the heart's shape and segmenting its components into the Myocard, Left Ventricle, and Right Ventricle.

3.2 Econometric Analysis

This study undertakes an econometric examination Figure 5 of the medical technology sector, highlighting investment patterns, evolutionary trends, and innovation velocities. The core objective is to decipher the economic ramifications of employing the YOLOv5 deep learning model in cardiac imaging [16] We delve into the potential economic advantages and drawbacks that come with this technological adoption. Our findings provide a clear perspective on the economic feasibility of integrating the YOLOv5 model, aiding healthcare policymakers in crafting economically sound decisions that uplift patient care and optimize healthcare outcomes. Within the scope of the entrepreneurial ecosystem, an econometric analysis shines light on the interplay of varied variables and their influence on entrepreneurial progress. The surge in adoption of such efficient technologies by startups or established entities within the ecosystem can induce significant sectoral transformations.

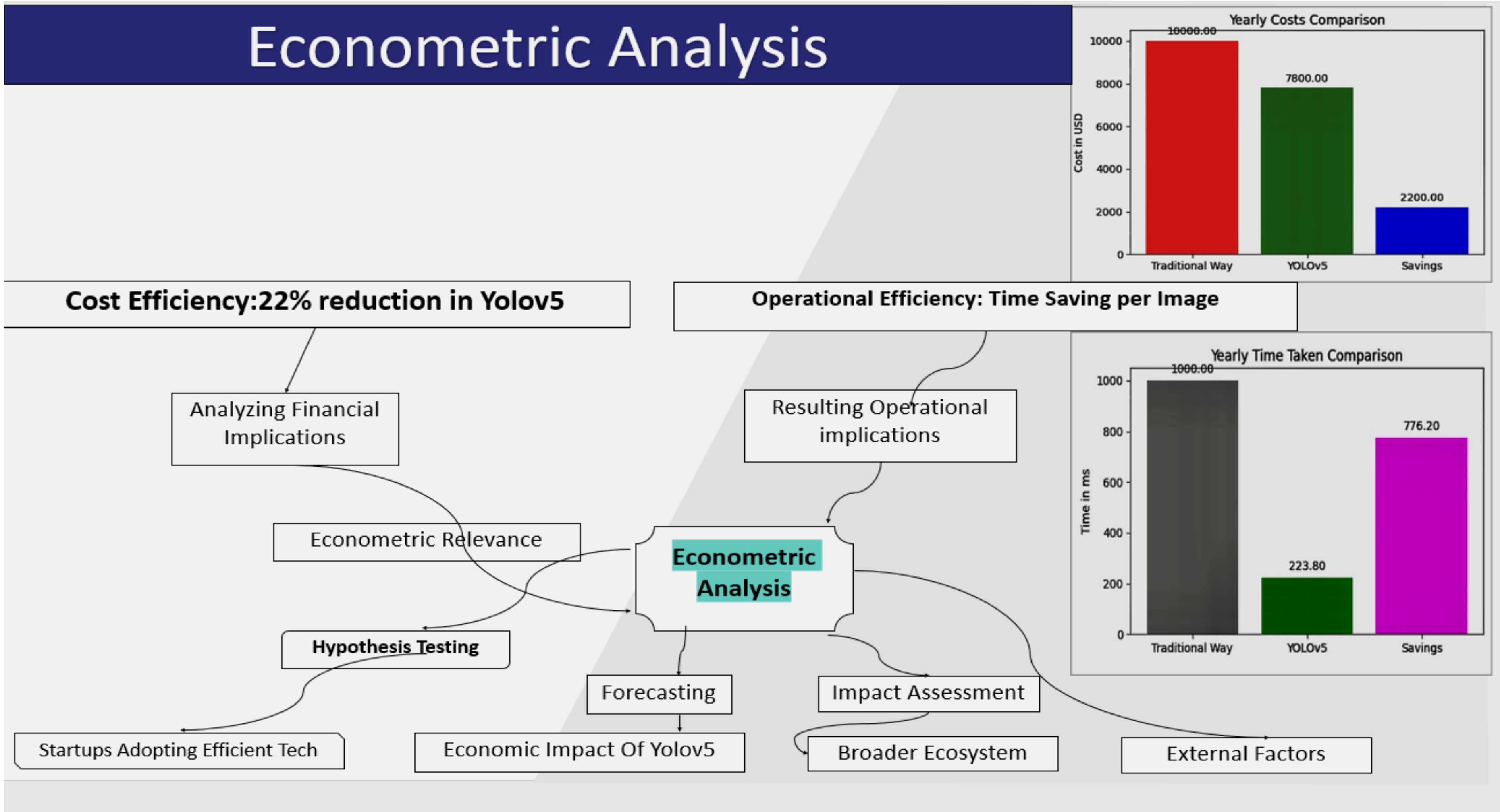

Figure 5: Econometric Analysis

The study, by examining investment behaviors, innovative trends, and patterns, delves deep into understanding the economic repercussions of harnessing the YOLOv5 deep learning model for cardiac imaging, all the while keeping an eye on enhanced patient care and weighing the economic aspects.

Hypothetical Cost-Benefit Analysis

Traditional Method: Costs $1 per image, taking 100ms per image.

Using YOLOv5: Cost is linked to its inference time of 22.3ms.

Assuming an annual processing of 10,000 images:

- Annual Expenditure with Traditional Method: $10,000
- Annual Expenditure with YOLOv5: $7,800
- Annual Cost Savings: $2,200
- Daily Cost Reduction: $6.03
- Annual Time Consumption using Traditional Method: 1,000 seconds
- Annual Time Consumption using YOLOv5: 223.8 seconds
- Daily Time Reduction: 2.13 seconds

may cause out-of-memory errors on GPUs with limited memory. also, karnel may crush during the run of code. For this it will take long time to get outcome by running the single cell of code.

3.3 Data Preprocessing

Data preprocessing is a crucial preparatory step for YOLOv5 implementation in 3D heart imaging segmentation using MRI scan images. Properly pre-processed data ensures that the YOLOv5 model[18] can effectively learn and accurately segment the cardiac structures of interest, such as the myocardium, right ventricles, and left ventricles, leading to improved diagnostic accuracy and treatment planning in cardiac healthcare. The key data preprocessing steps for YOLOv5 implementation in 3D heart imaging segmentation are as follows.

1. *Image Resampling and Alignment:* Since MRI scan images can have varying voxel sizes and resolutions, it is essential to resample and align them to a standardized 3D grid. This process ensures that all images have consistent spatial dimensions, which is crucial for the YOLOv5 model to process the data correctly.

2. *Intensity Normalization:* MRI scan images may have different intensity ranges due to variations in imaging protocols and scanners. Normalize the intensity values of the images to a common range, typically [0, 1], or standardize them using techniques such as Z-score normalization. Normalization mitigates the impact of intensity variations on the model's performance and helps achieve more consistent segmentations.
3. *Annotation Format Conversion:* Convert the ground truth annotations of the MRI scan images to the format compatible with the YOLOv5 model's requirements. YOLOv5 typically uses bounding box annotations where the coordinates and dimensions are relative to the image size.
4. *Data Split:* Divide the pre-processed dataset into training, validation, and testing sets. The training set is used to train the model, the validation set is used for hyperparameter tuning, and the testing set is used to evaluate the model's performance on unseen data.
5. *Data Loader:* Implement a data loader that efficiently loads and pre-processes the MRI scan images and their corresponding annotations during model training. The data loader should handle batch processing, shuffling, and data augmentation, ensuring that the correct association of images and annotations is maintained.

3.4 Statistical Analysis

The examiner of all data was conducted using Python program. The main objective is to scrabble into its quantitative dimensions. By deploying a range of statistical methods Fig.6 , including precision, recall, F1 score, hypothesis testing, data distribution analysis, cross-validation, learning rate scheduling, and Bayesian optimization, researchers aimed to bolster the reliability, precision, and robustness of the YOLOv5 implementation.

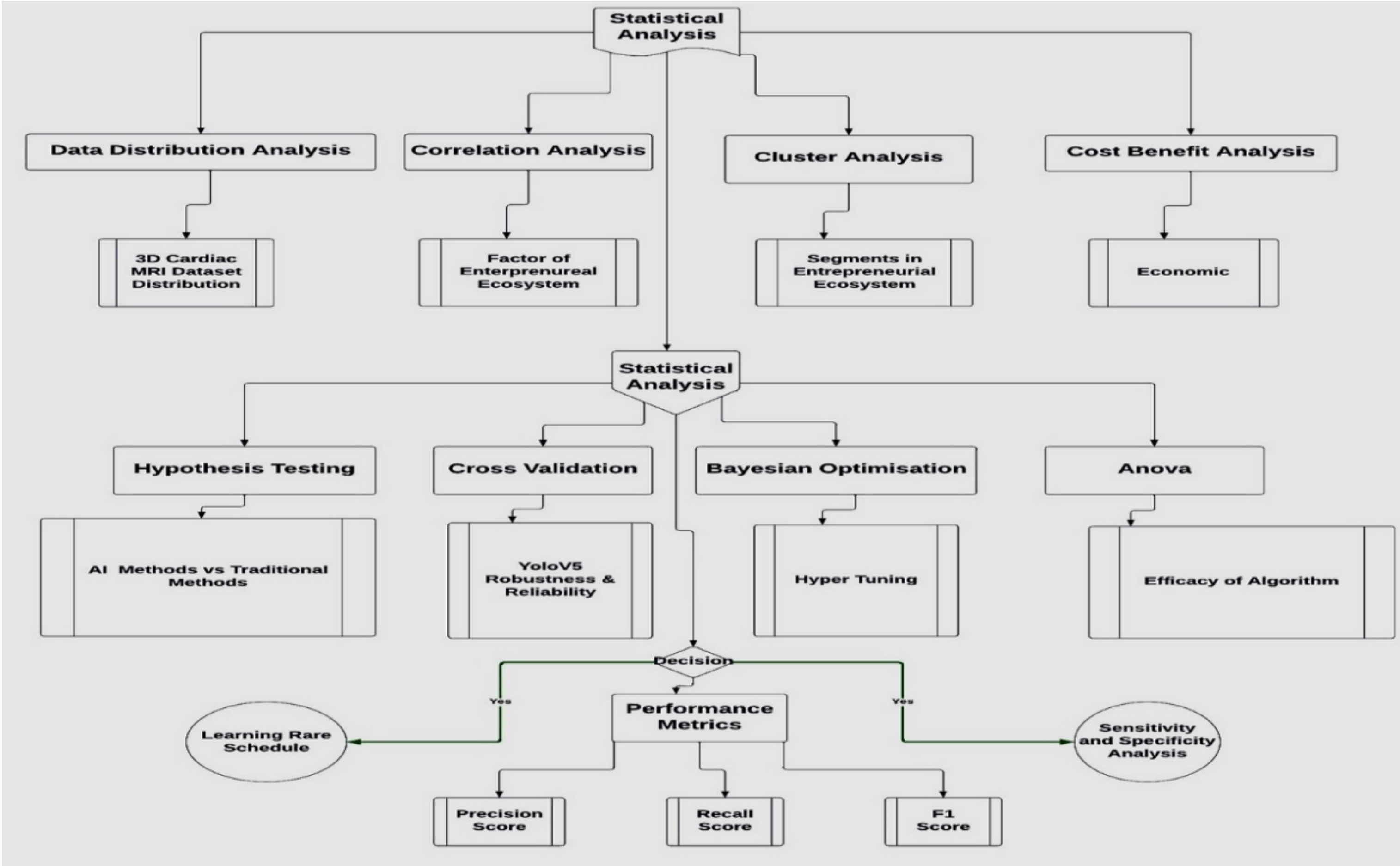

Figure 6: Statistical Analysis Framework

By employing these statistical methods, this analysis provides insights into the characteristics of heart imaging data, identifies patterns or anomalies, and evaluates the effectiveness of imaging techniques in diagnosing and assessing cardiac conditions. The findings contribute to evidence-based decision-making in clinical practice and inform research actions and support the advancement of 3D heart imaging technology to improve patient care and outcomes in cardiology. Analytically the identified parameters are varied one at a time while keeping other parameters constant.

3.5 Ethical Considerations

The research complies with ethical guidelines. Publicly available data is used to ensure individual privacy is not compromised. As these models hold significant potential in improving cardiac diagnosis and treatment, it is essential to address ethical concerns to ensure patient safety, privacy, and equitable access to healthcare. By prioritizing informed consent, privacy protection, equitable access, accuracy, and transparency, we can ensure the responsible and ethical use of these models in cardiac diagnosis and treatment. Integrating ethical considerations into the design, implementation, and governance of 3D heart imaging models fosters patient trust, safeguards privacy, and promotes equitable healthcare delivery.

4. MODEL IMPLEMENTATION

We employed the YOLOv5 deep learning model for segmenting 3D heart images, with a particular emphasis on delineating the myocardium, right ventricles, and left ventricles. Renowned for its precision and effectiveness in object detection and segmentation, the YOLOv5 model serves as a tool to pinpoint and segment these cardiac components accurately. To enhance usability, this implementation is showcased within a Streamlit framework. This interactive platform lets users effortlessly upload 3D cardiac images and view the segmented results. Figure 7 is model implementation and product implementation steps.

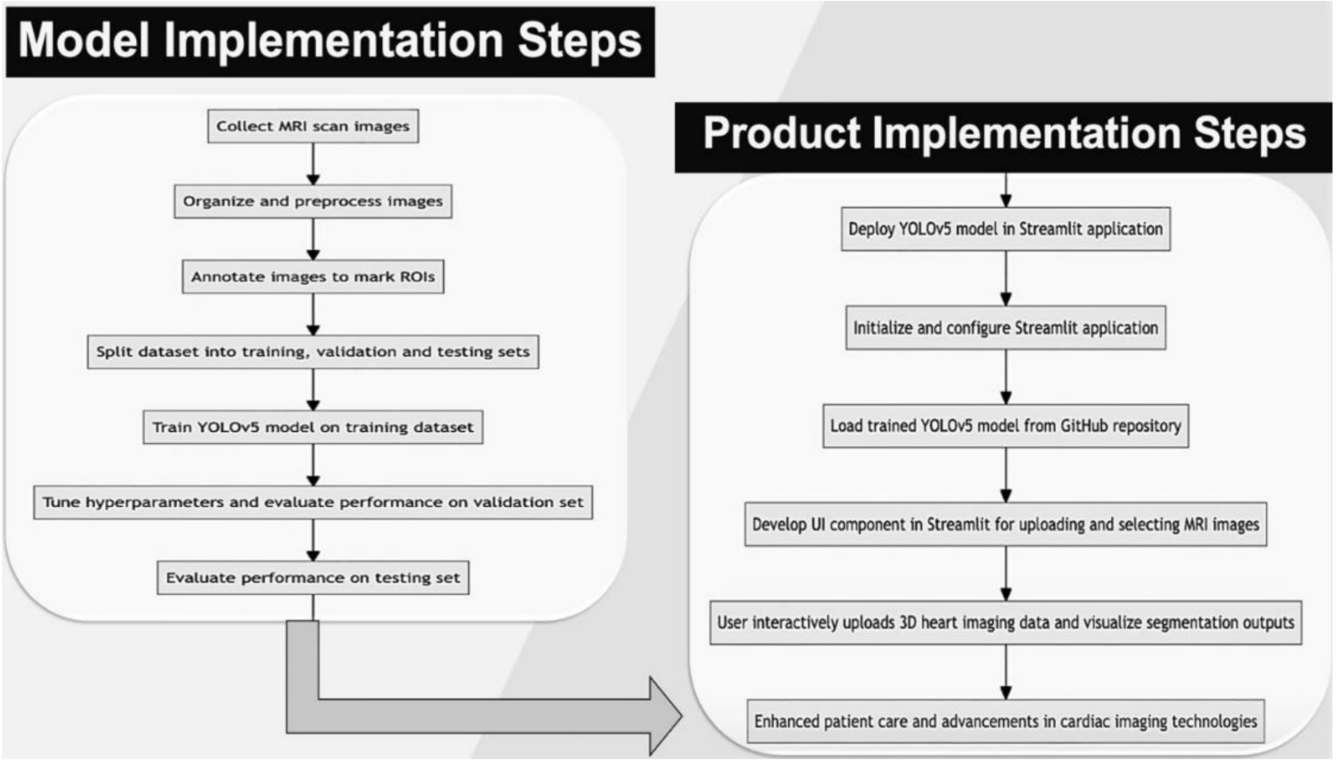

Figure 7: Model & Product Implementation Steps

4.1 Data preparation

Data preparation is a crucial step in deploying the YOLOv5 deep learning model for 3D heart imaging segmentation using MRI scan images. This process involves collecting, organizing, and pre-processing the data to ensure optimal model performance and accurate segmentation results. Collected an open-source dataset of MRI scan images that include the necessary cardiac structures for segmentation, such as myocardium, right ventricles, and left ventricles. Also, ensured the dataset covers a diverse range of patients, encompassing different cardiac conditions and imaging variations. The dataset images are annotated to mark the regions of interest (ROI) and ensured accurate delineation of the target structures by carefully collecting, pre-processing, and organizing the data, we can ensure optimal model performance, accuracy in segmentation, and reliable results.

This well-prepared dataset sets the foundation for training and deploying the YOLOv5 model, enabling accurate and efficient segmentation of the myocardium, right ventricles, and left ventricles in MRI scan images.

4.2 Model Development and Training

The development of the YOLOv5 model for 3D heart imaging segmentation using MRI scan images enables accurate identification and precise delineation of cardiac structures, including myocardium, right ventricles, and left ventricles. By following a meticulous development process, encompassing data collection, pre-processing, model architecture selection, training, evaluation, and optimization, the YOLOv5 model can provide valuable support for diagnosis, treatment planning, and analysis of cardiac conditions. The implementation of the model enhances patient care, aids medical professionals in their decision-making process, and contributes to advancements in the field of cardiology. The model training involves utilizing the prepared dataset by splitting the MRI scan images and their corresponding annotations into training, validation, and testing sets. The training set is used to train the model, while the validation set is used for hyperparameter tuning and performance evaluation. The YOLOv5 model is trained with each combination on the training dataset and evaluates its performance on the validation set using metrics like Intersection over Union, precision, recall, F1 score, or mean average precision. Keep track of the evaluation metrics for each hyperparameter combination to compare performance across iterations. The hyperparameters and their corresponding evaluation metrics are recorded to analyze the model's behavior with different configurations. After selecting the best hyperparameters, evaluate the model's performance on the testing set to obtain an unbiased assessment of its segmentation accuracy on unseen data.

4.3 Model Deployment in Streamlit

The deployment process of the YOLOv5 deep learning model for 3D heart imaging segmentation using MRI scan images, specifically using the Streamlit framework. The YOLOv5 model, known for its accuracy and efficiency in heart segmentation tasks, is deployed within a Streamlit application to accurately identify and segment cardiac structures, including the myocardium, right ventricles, and left ventricles. This implementation provides a user-friendly interface for clinicians and researchers to interact with the model and visualize the segmentation results. The necessary development environment is established using the required Python library dependencies for the YOLOv5 model deployment. Then, the Streamlit application is initialized and configured with the required settings. The trained YOLOv5 model is loaded, using the GitHub repository within the Streamlit application. The GitHub repository has a developed AI model file, and a Python code is developed to use the AI model as a Streamlit application using Python libraries essential for the implementation. A user interface component python-Streamlit code is developed in the Streamlit application to allow users to upload MRI scan images for segmentation and an additional feature of choosing the scanned image from the test set. The Streamlit deployment streamlines the user experience, making the model accessible and usable for medical professionals, ultimately enhancing patient care, and advancing cardiac imaging technologies.

5. RESULTS

A confusion matrix is a performance evaluation tool that provides a comprehensive summary of the model's predictions compared to the ground truth annotations. The confusion matrix is particularly useful for understanding the model's accuracy, identifying areas of misclassification, and assessing the overall performance of the segmentation task. The confusion matrix Fig.8 is a square matrix with rows and columns corresponding to the different classes (e.g., myocardium, right ventricles, left ventricles). It is organized as follows:

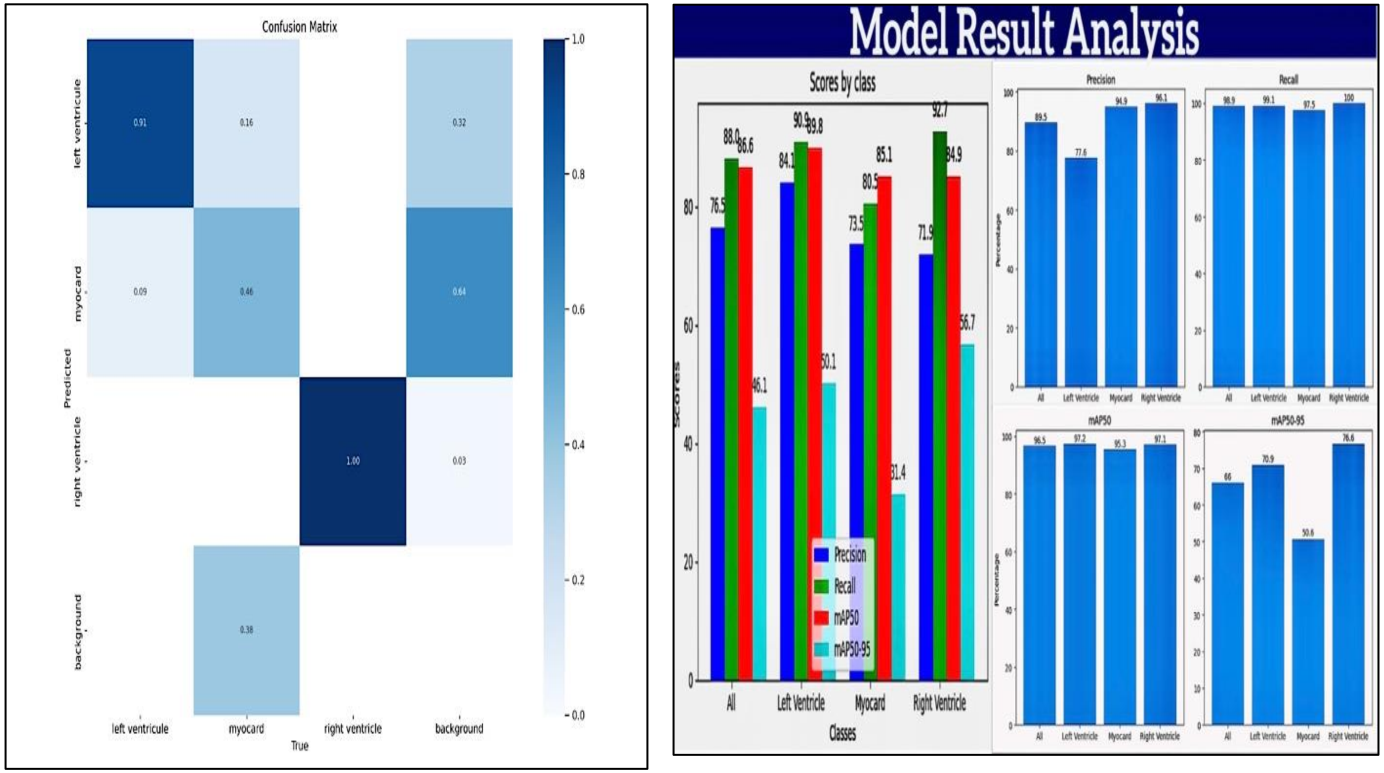

Figure 8: Confusion matrix of the 3D heart imaging model & Score Visualisation

Using the information from the confusion matrix, several performance metrics can be calculated, such as precision, recall (sensitivity), specificity, F1 score, and accuracy (Figure 9) . These metrics provide insights into the model's ability to accurately segment each class and its overall performance on the 3D heart imaging segmentation task. By analysing the confusion matrix and associated metrics, researchers and medical professionals can gain a deeper understanding of the strengths and limitations of the YOLOv5 implementation for 3D heart imaging segmentation, facilitating improvements and optimizations as needed. The F1 Confidence curve is a visual representation of how the F1 score (harmonic mean of precision and recall) varies with different confidence thresholds in the YOLOv5 implementation for 3D heart imaging segmentation of MRI scan images. The confidence threshold is a crucial parameter that determines the confidence level required for the model to make a prediction. By adjusting this threshold, we can control the trade-off between precision and recall. The F1 Confidence curve illustrates how the F1 score changes as the confidence threshold increases. Typically, as the threshold increases, the model becomes more conservative in making predictions, resulting in higher precision but lower recall. This is because the model only makes predictions when it is highly confident about the segmentation. As a result, the F1 score may increase at higher confidence thresholds due to improved precision but may decrease due to decreased recall. Researchers and medical professionals can analyse the F1 Confidence curve to determine the optimal confidence threshold that balances precision and recall for their specific application. The threshold that maximizes the F1 score is often considered the best balance between accurate segmentation and minimizing false positives and false negatives. Additionally, the F1 Confidence curve allows users to visualize the model's performance across different confidence levels, helping to understand its behaviour various clinical scenarios.

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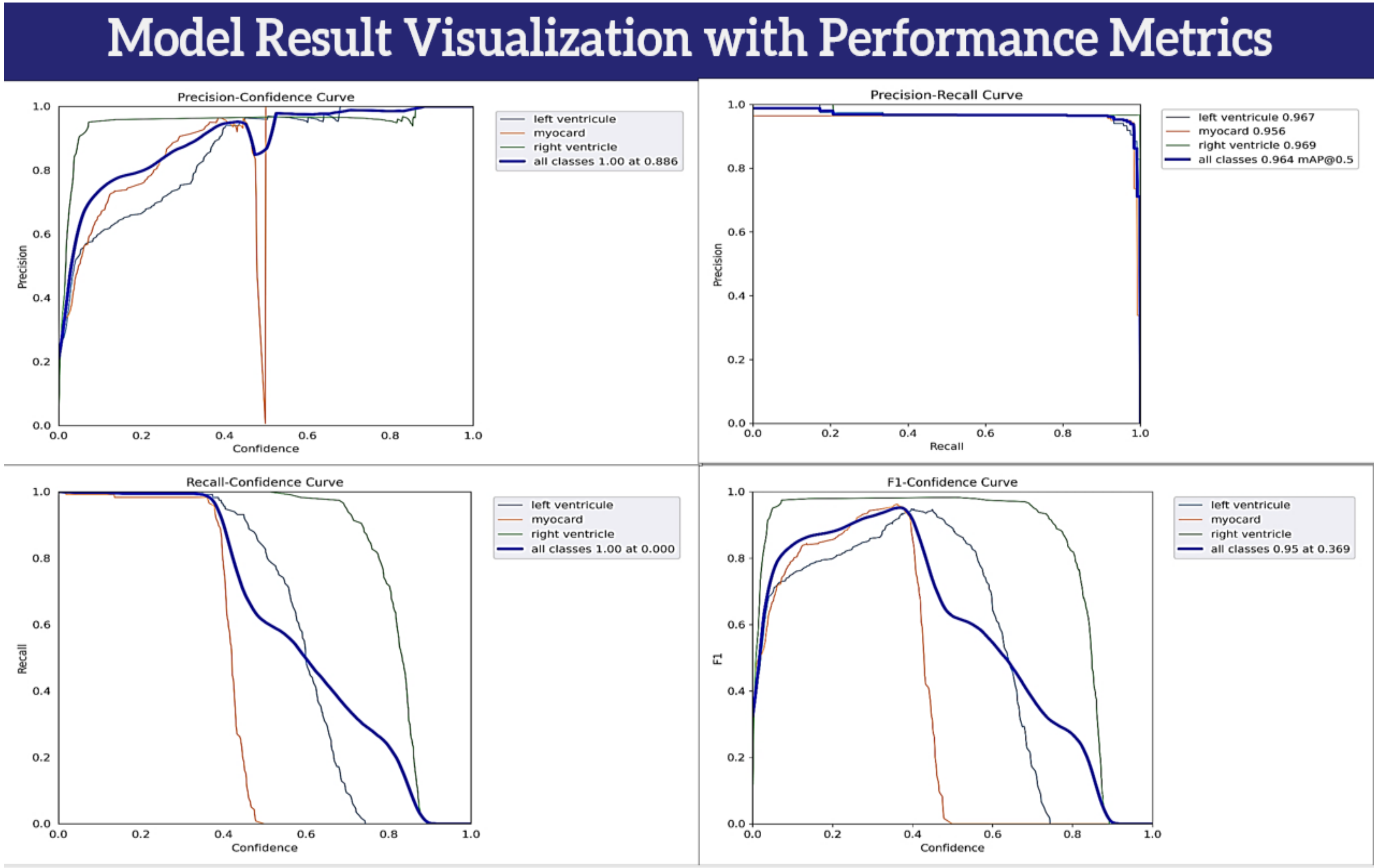

Figure 9: Precision, Recall, F1- Confidence Curve of the 3D heart imaging model

By examining the F1 Confidence curve, researchers can gain insights into the trade-offs between precision and recall and fine-tune the YOLOv5 model's confidence threshold to achieve the desired segmentation performance in 3D heart imaging segmentation of MRI scan images.The Precision-Recall (PR) curve is a graphical representation of how the precision and recall metrics vary with different confidence thresholds in the YOLOv5 implementation for 3D heart imaging segmentation of MRI scan images. The PR curve is a valuable tool for evaluating the model's performance, particularly when dealing with imbalanced datasets or varying confidence levels. Similar to the F1 Confidence curve, the confidence threshold is initially set to its default value (usually 0.5) and then gradually increased in small increments up to its maximum value (typically 1.0). At each confidence threshold, the YOLOv5 model makes predictions on the 3D heart MRI scan images and generates segmentation results for each class (e.g., myocardium, right ventricles, left ventricles). For each confidence threshold, the precision and recall metrics are calculated for each class. Precision measures the proportion of true positive detections among all positive predictions, while recall measures the proportion of true positives detected from all ground truth positives. The Precision-Recall curve illustrates the trade-off between precision and recall as the confidence threshold changes. Typically, as the threshold increases, the model becomes more conservative in making predictions, leading to higher precision but lower recall. On the other hand, lowering the threshold may increase recall but could decrease precision due to more false positives. The curve's shape can provide insights into the model's performance. A curve that is closer to the top-right corner indicates a better overall segmentation performance, where both precision and recall are high across a wide range of confidence thresholds. The area under the Precision-Recall curve (AUC-PR) is a single scalar metric that summarizes the model's overall performance. A higher AUC-PR value indicates a model with better precision-recall balance and overall segmentation accuracy. Researchers and medical professionals can use the Precision-Recall curve Figure10 to determine the optimal confidence threshold that achieves the desired balance between precision and recall for their specific application. The threshold that maximizes both precision and recall is often considered the best trade-off.

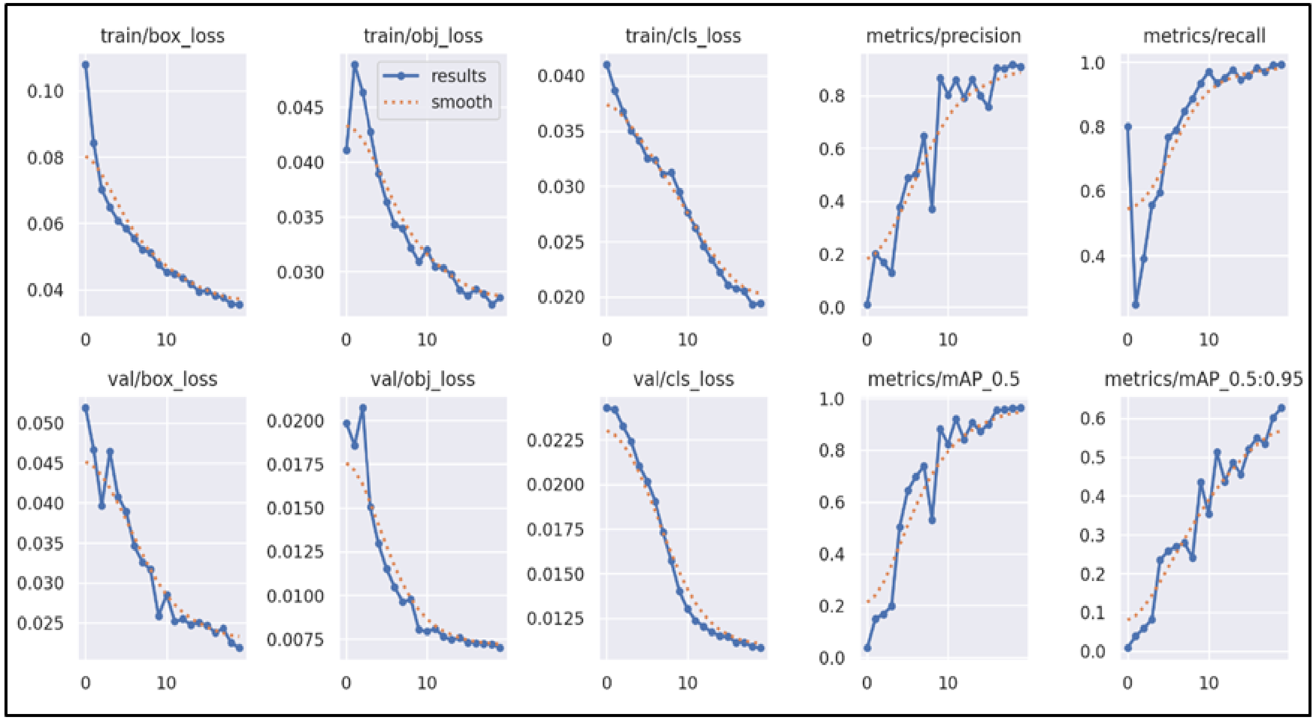

Figure 10: Epoch Result Curve of the 3D Heart Imaging Model

The "train/box_loss" is a measure of the discrepancy between the predicted bounding box and the ground truth bounding box. It quantifies how well the model is estimating the location and size of the object within the image. During the model training process, the "train/box_loss" is minimized through gradient descent optimization. By minimizing this loss, the model learns to accurately predict the bounding box coordinates for different objects in the image, leading to improved object detection performance. The loss function for bounding box regression is the Mean Squared Error (MSE) loss. Given the ground truth bounding box coordinates (x, y, width, height) and the predicted bounding box coordinates (x', y', width', height'), the MSE loss is calculated as follows:

$$\textbf{MSE loss} = (x - x')^2 + (y - y')^2 + (\mathrm{sqrt}(width) - \mathrm{sqrt}(width'))^2 + (\mathrm{sqrt}(height) - \mathrm{sqrt}(height'))^2. \quad [1]$$

The "obj_loss" is associated with the detection of objects within an image and measures how well the model predicts the presence of objects in different regions of the image. The "obj_loss" is often calculated using the Binary Cross Entropy (BCE). For each grid cell, the model outputs a confidence score representing the probability of an object's presence. The ground truth label for this confidence score is 1 if an object is present in the grid cell (positive sample) and 0 if no object is present (negative sample). The BCE loss is then calculated as follows:

BCE loss=-(y*log(p)+(1-y) *log(1-p)). **[2]**

where y is the ground truth label (0 or 1) and p is the predicted confidence score (a value between 0 and 1) from the model. During the model training process, the "train/obj_loss" is minimized through gradient descent optimization. By minimizing this loss, the model learns to accurately predict the presence or absence of objects in different grid cells, contributing to improved object detection performance in YOLOv5.The "cls_loss" is associated with the task of predicting the class or category of the detected objects within an image. In YOLOv5, the model predicts the class probabilities for each bounding box that it detects. For example, in the case of 3D heart imaging segmentation, the classes could be "myocardium," "right ventricles," "left ventricles," or any other relevant categories. The "cls_loss" is commonly calculated using the Cross-Entropy loss (also known as Logarithmic Loss). This loss function is suitable for multi-class classification tasks, where each bounding box is associated with multiple class probabilities.

Here's how the "cls_loss" is typically calculated:

Cross-Entropy Loss = -∑ (y * log(p)) **[3]**

y is a one-hot encoded ground truth label for the true class of the detected object. It is a vector with zeros in all entries except for the true class, which is marked with a 1.
p is the predicted class probabilities for the detected bounding box. These probabilities are calculated using the SoftMax function, which converts raw scores into probability values that sum up to 1. During training, the YOLOv5 model aims to minimize the "train/cls_loss" by adjusting the weights and biases of the neural network through gradient descent optimization. This process enables the model to accurately predict the class probabilities for each bounding box and improve its object classification performance. The "metrics/precision" refers to one of the performance evaluation metrics used to assess the model's accuracy in making positive predictions (detections) correctly. Precision is a measure of how many of the predicted positive samples (true positives) are correct out of all the positive predictions made by the model (true positives + false positives). It quantifies the ability of the model to avoid false positives, meaning instances where the model incorrectly classifies a negative sample as a positive one.
The precision metric is calculated as follows:

Precision = True Positives / (True Positives + False Positives) **[4]**

True Positives (TP) represent the number of correctly predicted positive samples (correctly detected objects) by the model.
False Positives (FP) represent the number of negative samples (non-objects) that are incorrectly classified as positive samples (false detections) by the model.

A high precision value indicates that the model is good at avoiding false positives and is confident when making positive predictions. The "metrics/recall" refers to one of the performance evaluation metrics used to assess the model's ability to correctly detect positive samples (true positives) out of all the ground truth positive samples in the dataset. Recall, also known as sensitivity or true positive rate (TPR), quantifies the percentage of true positive samples that the model correctly identifies out of all the positive samples present in the dataset.

The recall metric is calculated as follows:

Recall = True Positives / (True Positives + False Negatives) **[5]**

True Positives (TP) represent the number of correctly predicted positive samples (correctly detected objects) by the model. False Negatives (FN) represent the number of positive samples (objects) that the model fails to detect. A high recall value indicates that the model can effectively detect most of the positive samples in the image, minimizing the number of false negatives or missed detections. It's essential to consider both precision and recall metrics together to evaluate the model's overall performance. The “mAP” is a commonly used performance metric to evaluate the accuracy of object detection models. It considers both precision and recall across different confidence thresholds and IoU thresholds. IoU measures the overlap between the predicted bounding boxes and the ground truth bounding boxes. For each class (e.g., myocardium, right ventricles, left ventricles), calculate the precision and recall at different confidence thresholds. The confidence threshold determines the minimum confidence required for the model to make a positive detection. The IoU threshold of 0.5 is a common standard in object detection evaluation. It means that a predicted bounding box is considered correct if the IoU with the corresponding ground truth bounding box is at least 0.5. The” mAP 0.5” is a crucial metric as it provides a comprehensive assessment of the model's accuracy in detecting objects at a specific IoU threshold. A higher mAP of 0.5 indicates that the model performs well in both precision and recall for the detected objects, with a sufficient level of bounding box overlap with the ground truth. This metric helps to quantify the overall segmentation accuracy and is essential for assessing the performance of the model in medical imaging applications. A correlogram Figure 11 in the context of the 3D heart imaging model based on height, width, x, and y represents the correlation between these specific features used for cardiac structure segmentation. Let's break down each feature: The height feature represents the vertical size of the bounding box (segmentation mask) that encompasses the cardiac structure in the MRI scan image. The width feature represents the horizontal size of the bounding box (segmentation mask) that encompasses the cardiac structure in the MRI scan image. The x-coordinate represents the horizontal position of the centre of the bounding box in the MRI scan image. The y-coordinate represents the vertical position of the center of the bounding box in the MRI scan image.

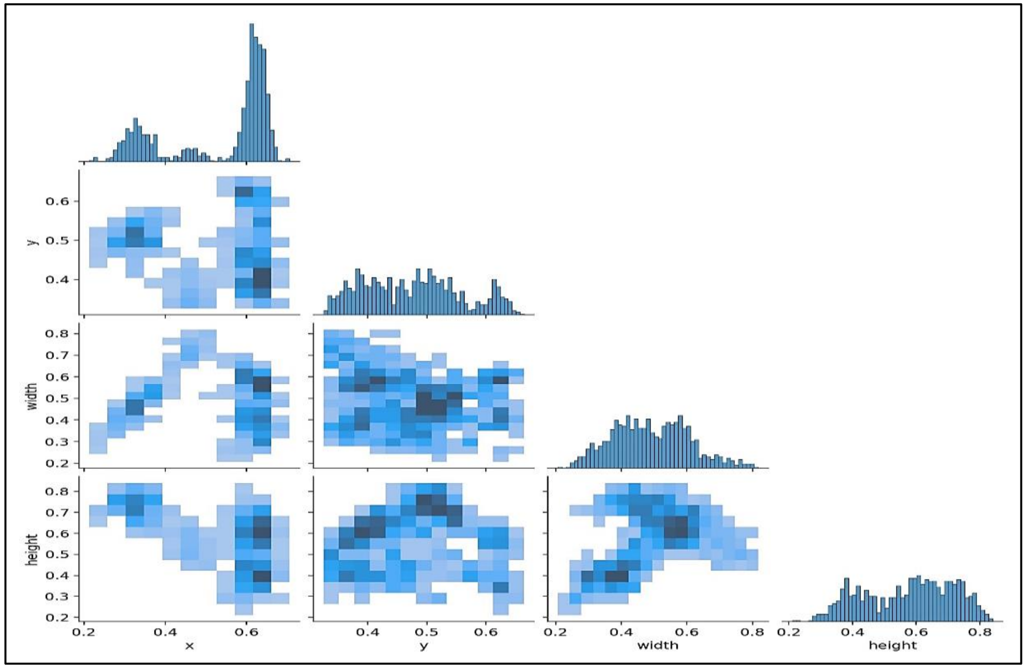

Figure 11: Correlogram of the 3D Heart Imaging Model

A correlogram based on these features would show the correlation coefficients between height, width, x, and y for the bounding boxes (segmentation masks) used to identify and locate the cardiac structures (myocardium, right ventricles, left ventricles) in the 3D heart imaging model. The correlogram based on height, width, x, and y features provides insights into how these attributes relate to each other for each cardiac structure. Strong positive correlations between height and width, for example, suggest that larger bounding boxes tend to have larger widths and vice versa. The correlation coefficients are visualized as a matrix, where each cell represents the correlation between two features. In this case, the matrix will show the correlation between height, width, x, and y for each cardiac structure. As mentioned before, the correlation coefficients are often color-coded to indicate the strength and direction of the correlation. Positive correlations may be represented with shades of blue, while negative correlations are represented with shades of darker blue. The intensity of the colour reflects the strength of the correlation, with darker shades indicating stronger correlations. Similarly, correlations between x and y could indicate how the centre of the bounding box tends to be positioned in relation to its height and width. Analysing the correlogram can help identify relationships between these features and guide decisions such as feature selection, data pre-processing, or model optimization in the 3D heart imaging model. The correlogram based on height, width, x, and y features in the 3D heart imaging model provides valuable insights into the relationships between these attributes and can help improve the accuracy and efficiency of the cardiac structure segmentation process.

5.1 Instance Segmentation

Instance segmentation Figure 12 in the context of 3D heart imaging refers to a computer vision technique that aims to identify and distinguish individual instances (objects) of cardiac structures within a 3D MRI scan image. Unlike semantic segmentation, which assigns a single label to each pixel or voxel in the image, instance segmentation goes a step further by providing a unique identifier for each separate instance of a cardiac structure, such as the myocardium, right ventricles, and left ventricles. The instance segmentation process involves the following steps: The first step is to identify potential objects (cardiac structures) within the 3D MRI scan image. Object detection algorithms are utilized to detect and localize the bounding boxes that encompass each cardiac structure. Once the bounding boxes are detected, instance segmentation algorithms are applied within each box to segment the individual cardiac structures. These algorithms typically generate binary masks or voxel maps, where each pixel or voxel belonging to a specific structure is labelled with a unique identifier. After the segmentation is complete, each segmented instance is assigned a distinct label or identifier to differentiate it from other instances of the same or different structures. This labelling allows for easy identification and tracking of each cardiac structure separately. The primary goal of instance segmentation is to precisely outline the boundaries of each cardiac structure and differentiate them from one another, allowing for accurate and detailed segmentation results. This level of granularity is particularly useful in medical imaging and clinical applications where a precise understanding of individual structures is necessary for accurate diagnosis and treatment planning.

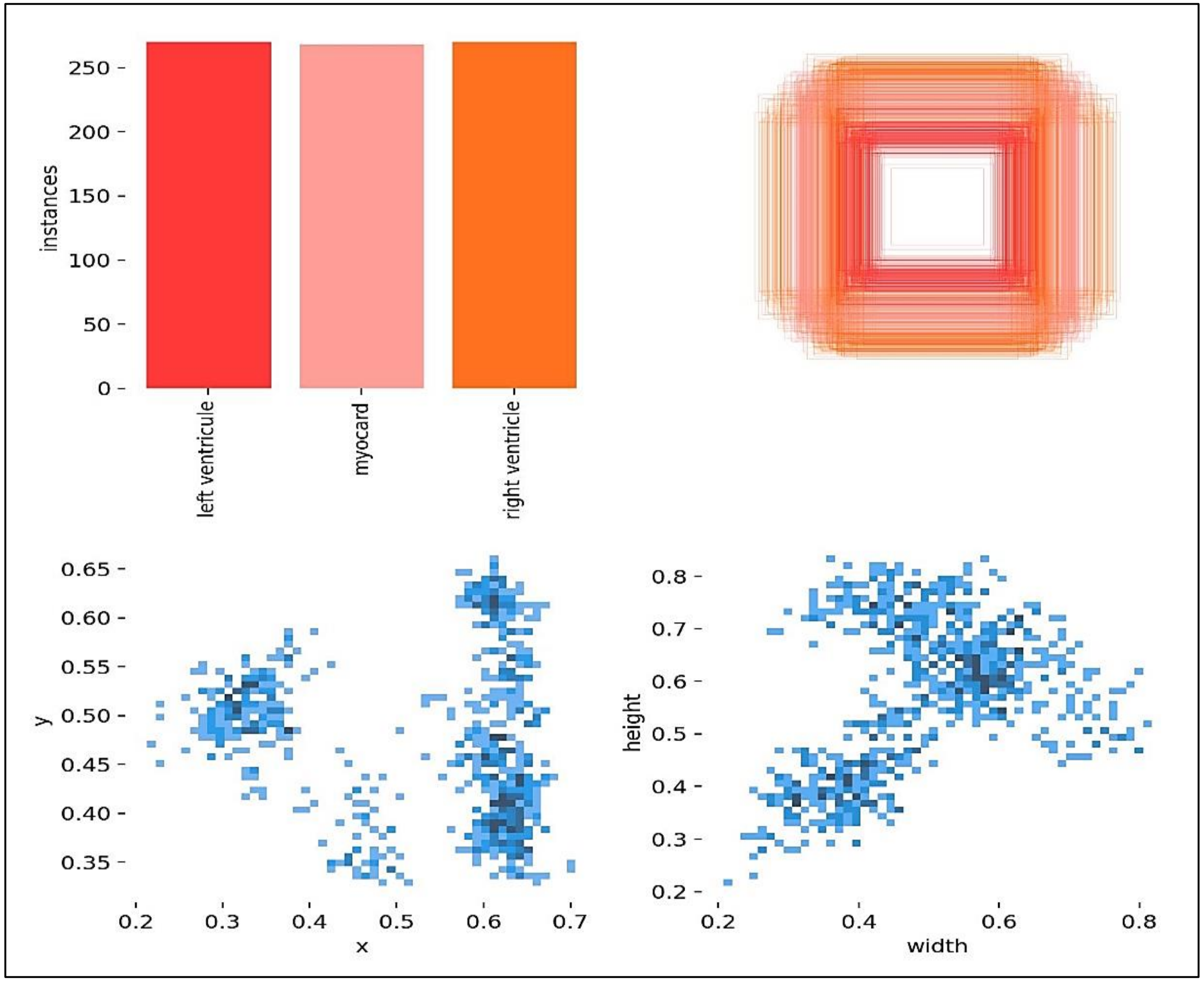

Figure 12: Instance Segmentation Of 3D Heart Imaging Model

5.2 “Streamlit Dashboard for 3D Heart Imaging Application”

The Streamlit dashboard Fig. 13 titled "3D Heart Imaging App" is designed to interact with the YOLOv5 model for 3D heart imaging segmentation. It provides multiple options for selecting image sources, allowing users to visualize the model's predicted heart segmentation on different types of images. Here's how the dashboard works: The dashboard has a clear title "3D Heart MRI Image Segmentation", which immediately communicates its purpose to the users. The dashboard includes a selection panel where users can choose the source of the images they want to use for segmentation. There are three options available: **"From the Sample Images"** This option presents users with a set of pre-defined sample 3D MRI scan images of the heart. These sample images are provided within the dashboard to serve as demonstration data. *"***Upload Your Own Image***":* With this option, users can upload their own 3D MRI scan images of the heart from their local machine. This feature enables users to work with real patient data or custom images for segmentation. **"Select Random Image from the Test Set":** This option allows users to explore the model's segmentation performance on unseen data. The dashboard randomly selects an image from the test set, which consists of images not used during the model training phase. For the **"Select Random Image from the Test Set"** option, the dashboard includes a slider that enables users to cycle through different test set images. By sliding the slider, users can choose a specific test image and observe the model's segmentation results for that image. Once an image source is selected or an image is uploaded, the dashboard displays the chosen or uploaded 3D MRI scan image. Additionally, the dashboard shows the predicted heart segmentation image as the output visualization. The predicted heart segmentation is obtained from the YOLOv5 model's segmentation algorithm, which accurately detects and segments the cardiac structures (myocardium, right ventricles, left ventricles) in the input image. The segmented cardiac structures result shows the class name with the value of accuracy to the user. Streamlit provides an interactive environment, enabling users to effortlessly switch between different image sources and instantly visualize the model's segmentation results for the selected images. The overall workflow of the "3D Heart MRI Image Segmentation App" Streamlit dashboard ensures a seamless user experience in exploring and evaluating the YOLOv5 model's segmentation performance on various 3D MRI scan images of the heart. Users can easily interact with the dashboard, observe the predicted segmentation output, and use the results to aid medical professionals in analyzing and diagnosing cardiac structures for enhanced patient care.

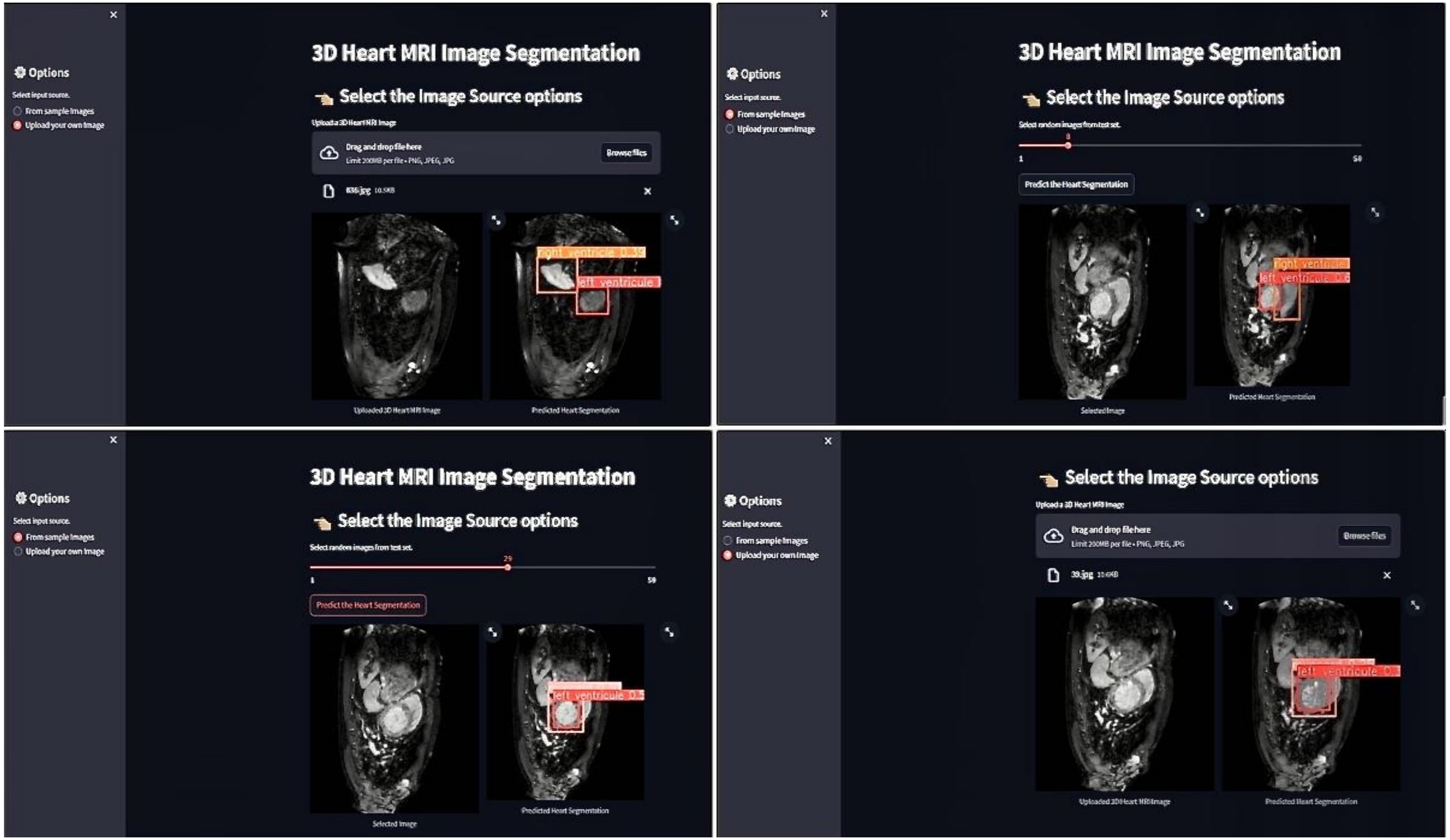

Figure 13: Streamlit Dashboard Showing the Predicted 3D Heart Segmentation

6. DISCUSSION

We have delved into the intricacies of this ecosystem and its profound impact on the adoption of 3D deep learning techniques. Our findings underscore the pivotal role played by the entrepreneurial ecosystem in driving innovation, as it comprises a collective effort involving entities such as funding sources, researchers, policymakers, and end-users, all contributing to the advancement of these cutting-edge techniques. The examined YOLOv5 model exhibits significant promise when applied to 3D MRI scans of the heart, particularly in accurately segmenting cardiac structures. This model, renowned for its efficiency and precision in heart segmentation tasks, can be tailored to identify and outline crucial cardiac components such as the myocardium, right ventricles, and left ventricles. This discourse underscores the significance and potential implications of employing this model within the context of 3D MRI scans of the heart. Accurate segmentation of cardiac structures holds paramount importance for precise diagnosis, effective treatment planning, and in-depth analysis of various cardiac conditions. The model provides a robust framework for automating the segmentation process, potentially streamlining the workflow for medical professionals. By accurately detecting and delineating the myocardium and ventricles, the model facilitates the quantification of essential parameters. Furthermore, the model's efficiency proves particularly advantageous in processing 3D MRI scan data, as it enables near real-time segmentation, thus enhancing the diagnostic process's overall efficiency. Such rapid diagnostics are indispensable in clinical settings where timely decision-making is imperative. However, it is essential to acknowledge the persisting challenges in training the model for 3D MRI scans of the heart. The acquisition of a diverse and representative dataset assumes paramount importance to ensure accurate segmentation across a spectrum of cardiac conditions and patient demographics. Additionally, the annotation process mandates expertise to precisely label the cardiac structures of interest. Addressing these challenges is imperative to ensure the model's performance remains reliable and applicable across various clinical scenarios.

The novelty of our paper lies in the pioneering integration of the YOLOv5 deep learning algorithm with 3D cardiac MRI imaging, embedded within an entrepreneurial ecosystem framework to accelerate innovation in cardiac care. Our methodological contribution, marked by the deployment of an AI-powered 3D Cardiac Imaging App developed through the Streamlit framework, represents a leap in diagnostic imaging by achieving a high accuracy rate of 96.4% in heart segmentation tasks. This advancement is a testament to our model's ability to interpret complex medical imaging data with precision that rivals traditional approaches. By addressing critical bottlenecks in data diversity and annotation quality, our research sets a new standard for automated, high-accuracy cardiac diagnostics, offering scalable solutions adaptable to evolving clinical and research environments. The scientific community gains an invaluable tool, offering insights into the interplay between economic viability and technological adoption in MedTech while signaling a shift towards more collaborative and cross-disciplinary efficacy. We also address from theoretically to practically by mentioned some authors work in different concept then we pick up our methodology which is exceptional and represent as novelty.

7. LIMITATIONS

Our research faces constraints stemming from our reliance on open-source datasets, potentially limiting the depth and scope of our analysis. It is essential to acknowledge that the applicability of our findings may be constrained by the specific datasets we employed. While the YOLOv5 deep learning model demonstrates significant power, it may exhibit suboptimal performance in rare or atypical cases. Furthermore, our network and policy analyses may not fully capture the intricate and dynamic nature of the entrepreneurial ecosystem within the medical technology field. Given the rapidly evolving landscape of both medical technology and deep learning, it is possible that certain aspects of our findings could become less pertinent over time. The model's performance is intricately tied to the quality and representativeness of the training data and procuring a well-annotated dataset encompassing a wide spectrum of cardiac conditions, imaging protocols, and patient demographics can pose considerable challenges, requiring substantial time and effort. To address these limitations effectively, further research and development efforts are warranted. These should encompass the availability of high-quality annotated datasets, advancements in algorithms capable of handling complex cardiac structures, and optimization techniques aimed at bolstering the model's performance when processing 3D MRI scan images.

8. CONCLUSION

Our research study effectively investigated the key components of entrepreneurial ecosystems that play a pivotal role in facilitating innovation within the realm of cardiac imaging. Leveraging these ecosystem elements, we successfully implemented 3D deep learning techniques, with a particular focus on the YOLOv5 model, yielding notable outcomes with an approximate accuracy rate of 96.40%. These findings underscore the efficacy and potential of integrating deep learning methodologies into the medical technology sector, specifically within the domain of heart imaging. Moreover, our project showcased how such technological advancements can positively influence the entrepreneurial ecosystem, stimulating investments, nurturing further innovation, and fostering the development of new skill sets. The insights garnered from our research have the potential to provide valuable guidance for policymaking aimed at enhancing support for entrepreneurial ecosystems within the medical technology field. While acknowledging certain limitations, notably our reliance on available data and the potential evolution of the entrepreneurial landscape, our study lays a robust foundation for future exploration. Furthermore, it is worth noting that the YOLOv5 model holds substantial promise for enhancing the segmentation of cardiac structures in 3D MRI scan images of the heart. Its efficiency, speed, and potential for automation render it an asset in the field of cardiac imaging. To harness its full potential, future research, and development efforts, coupled with collaborations among experts in both medical imaging and deep learning, can contribute to refining and optimizing the model for even more precise and efficient cardiac segmentation within 3D MRI scan images.

Declaration of Interest Statement:

We declare that there are no conflicts of interest regarding the submission of our paper titled: “Revolutionizing Cardiac Care: Exploring the Synergy Between Entrepreneurial Ecosystems and 3D Deep Learning for Enhanced Heart Imaging in MedTech” to the respected journal.

Ethics approval and consent to participate:

Not applicable. The study involved the analysis of publicly available data with no identifiable human information.

Consent for publication:

Not applicable. This manuscript does not contain any individual person's data.

Availability of data and materials:

The data that support the findings of this study are available on request to the author, but restrictions apply to the availability of these data, which were used under license for this study. Data are, however, available from the authors upon reasonable request.

Overview of the dataset:

In the dataset, there are three classes named Left Ventricle, Myocard, and Right Ventricle. This dataset is a 3D MRI heart image. There are 400 images.

Dataset Documentation: https://github.com/datascintist-abusufian/3D-Heart-Imaging-apps/blob/main/Dataset%20Documentation%203D%20heart%20imaging%20apps.pdf

Source: Roboflow

Workspace: memoire

Project: heart-segmentation-2

Version: 1

URL: https://universe.roboflow.com/memoire/heart-segmentation-2/dataset

Competing interests:

The authors declare that they have no competing interests.

Funding:

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Authors' contributions:

First author, Md Abu Sufian performed data cleaning, statistical analysis, Literature Review, model building, and the second author, Jayasree Varadarajan, contributed to the paper formatting, data collection, App development and entire paper review and further corrected the whole paper to interpretation under the guidance of the supervisory team. Md Abu Sufian drafted the manuscript, and all authors contributed to critical revisions of the paper and approved the final version for submission.

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