# Cardiovascular Health with Vision Transformers

Priyanka Kaushik
Dept. of CSE (AIML), CSE-APEX
Chandigarh University Chandigarh, India
kaushik.priyanka17@gmail.com
https://orcid.org/0000-0003-4766-8772

Aditya Mathur
Dept. of Pharmacy Lingayas Vidyapeeth
University Faridabad, India
adityamathur@lingayasvidyapeeth.edu.in

Sani Kumar
Dept. of CEA Mangalayatan University
Aligarh, India
sani.kumar@mangalayatan.edu.in

Akanksha Anand Saxena
Dept. of Physiotherapy Usha Martin
University Ranchi, India
akanksha@umu.ac.in

Aswathy P B
Dept. of Computer Science and
Engineering
Dhanalakshmi Srinivasan University
Coimbatore, India
aswathypb@dsce.ac.in

Dr. Deepak Jain
Director IQAC Dhanalakshmi Srinivasan
University Tamil Nadu, India
prof.djain@gmail.com

2024 4th International Conference on Advancement in Electronics & Communication Engineering (AECE) | 979-8-3503-6472-9/24/$31.00 ©2024 IEEE | DOI: 10.1109/AECE62803.2024.10911566

**Abstract—This study aims to revolutionize cardiovascular health detection by pioneering the integration of state-of-the-art technologies such as artificial intelligence (AI), wearable devices, and genetic screening into a cohesive framework. This innovative approach seeks to enhance cardiovascular disease detection and intervention methods by combining AI algorithms for robust data analysis, wearable devices for continuous real-time monitoring of crucial physiological parameters, and genetic screening for personalized risk assessment. By pushing the boundaries of interdisciplinary research and adopting novel methodologies, this project aims not only to identify preventive strategies and personalized treatment options but also to fundamentally transform the entire paradigm of cardiovascular healthcare delivery.**

***Keywords—Cardiovascular Health, Cardiovascular Disease, Vision Transformers (VIT), Early Detection, Artificial Intelligence***

## I. INTRODUCTION

Cardiovascular health is a top priority in today's healthcare scene, affecting millions of people throughout the world. As the prevalence of heart problems rises, there is a pressing need for novel techniques to early identification and intervention. The project titled, "Revolutionizing Cardiovascular Health: Cutting-Edge Approaches to Detecting Heart Conditions," is a visionary venture that aims to reshape the cardiac health environment.

Cardiovascular disorders, which include conditions such as coronary artery disease and heart failure, place a substantial burden on individuals, families, and healthcare systems around the world. Despite advances in medical research, early detection of many illnesses remains a problem, frequently leading to delayed therapies and negative outcomes. Furthermore, the in- creasing prevalence of risk factors such as sedentary lifestyles, bad dietary habits, and aging populations exacerbates the problem, emphasizing the importance of preventative actions.

In response to these critical concerns, our project sets out on a mission to transform the way cardiac diseases are recognized, managed, and ultimately prevented. At its foundation is the combination of cutting-edge technology and medical experience, paving the way for proactive management and tailored care.

The project's objectives are varied, including a complete re- vamp of established detection procedures. The project's goal is to change the paradigm of heart health management by utilizing advances in artificial intelligence, wearable technologies, and genetic screening. The project's goal is to provide early detection, individualized therapies, and improved outcomes for anyone at risk of or impacted by cardiovascular disease by seamlessly integrating these technologies together.

The use of AI algorithms trained on large datasets is fundamental to the project's methodology since it allows for the accurate study of biomarkers including genetic predispositions, blood pressure patterns, and Electrocardiograms. These algorithms are effective instruments for risk assessment because they allow for the early identification of possible cardiac irregularities and provide guidance for customized therapies.

Moreover, the idea goes beyond conventional hospital settings, imagining wearable technology integrated into people's everyday lives. The project encourages a culture of active engagement in health management by providing people with the means to monitor their health in real time. Furthermore, genetic screening provides deep understanding of an individual's innate risks, allowing for customized lifestyle changes and targeted interventions based on genetic composition.

## II. LITERATURE SURVEY

The integration of deep learning methods in cardiovascular health monitoring has become a pivotal area of research, especially given the rising incidence of heart diseases globally.

This review summarizes recent advancements in utilizing deep learning and vision transformer (ViT) models for diagnosing and predicting cardiovascular conditions through various imaging modalities and data sources.

Deep Learning for ECG Analysis: Rath et al. (2021) investigated heart disease detection using deep learning algorithms applied to imbalanced ECG datasets [1]. Their work emphasized the challenges posed by data imbalance, which can significantly affect model performance. By employing advanced neural network architectures, they demonstrated improved diagnostic capabilities, highlighting the effectiveness of deep learning in processing complex biomedical signals.

Advances in Cardiac Imaging: The role of vision trans- formers in cardiac imaging has gained traction, particularly in segmentation tasks. Fan et al. (2023) introduced the ViT FRD model, which employs feature recombination distillation to enhance the accuracy of cardiac MRI image segmentation [2]. This innovative approach showcases how transformer architectures can provide superior results compared to traditional convolutional neural networks (CNNs) in medical imaging applications. Vafaeezadeh et al. (2024) conducted a review of ultrasound image analysis utilizing vision transformers, indicating a broader trend towards employing these models across various imaging techniques in cardiology. Their findings affirm that transformers are adept at extracting relevant features from ultrasound images, facilitating improved diagnostic accuracy. Job Satisfaction in Academic Settings: Sengar and Pandey (2024) conducted a study on the effect of job satisfaction on the performance of academic faculty in private institutions [3]. Their findings reveal a strong correlation between job satisfaction levels and faculty performance, suggesting that institutions should foster positive work environments to enhance overall productivity. This research adds valuable insights into human resource management practices within educational contexts. Multimodal Data Integration: The use of diverse data sources is essential for accurate cardiovascular disease diagnosis. Kim et al. (2016) explored a data mining approach that combined heart rate variability with carotid artery imaging [4]. This study highlights the importance of integrating different types of data to enhance predictive modeling, suggesting that a multimodal approach can yield richer insights into cardiovascular health.

Phonocardiogram Analysis: Abbas et al. (2022) focused on the automatic detection and classification of cardiovascular disorders by employing phonocardiogram signals along with convolutional vision transformers [5]. Their research indicates that acoustic signal analysis can provide a non-invasive alter- native for monitoring cardiovascular conditions, demonstrating the potential of deep learning to analyze sound data effectively. Hybrid Models and Novel Approaches: Recent studies have shown promising results with hybrid models that combine various machine learning techniques. Naidji and Elberrichi (2024) presented a hybrid vision transformer-CNN for detecting COVID-19 from ECG images [6]. This study illustrates the versatility of deep learning models in addressing various health challenges and suggests that hybrid approaches can enhance diagnostic performance.

AI in Recruitment and Selection Processes: Rathore (2023a) examined the transformative role of AI in recruitment and selection [7]. The study illustrates how AI technologies can streamline recruitment processes, reducing biases and enhancing efficiency. Rathore emphasizes the importance of ensuring that AI implementation is transparent and fair, highlighting the potential pitfalls that organizations must navigate to maintain equity in hiring practices.

Hybrid Models for Heart Disease Prediction: Naidu et al. (2021) developed a hybridized model that integrates various machine learning algorithms to enhance heart disease prediction [8]. Their approach effectively combines the strengths of different algorithms, resulting in improved accuracy and reliability in risk assessment. This study highlights the importance of hybrid techniques in addressing the complexities of cardiovascular conditions.

Vision Transformers in Digital Health: Al-hammuri et al. (2023) presented a comprehensive tutorial and survey on vision transformer architecture, specifically focusing on its applications in digital health [9]. They elucidate how vision transformers can process medical data with high efficiency and accuracy, showcasing their ability to capture intricate patterns in both images and signals. This research underscores the transformative potential of transformers in improving diagnostic processes.

Comparative Analysis in Cardiac Imaging: Granizo et al. (2024) conducted a comparative study examining the performance of vision transformers versus convolutional neural networks (CNNs) in cardiac image segmentation [10]. Their findings indicate that vision transformers often outperform CNNs in accurately segmenting cardiac structures, thanks to their capacity to handle complex data relationships. This analysis emphasizes the advantages of adopting transformer models in medical imaging tasks.

In another study, Rathore (2023b) assessed the efficacy of training strategies in improving productivity and career advancement within the Indian workforce [11]. The research indicates that strategic training initiatives, when augmented by AI-driven evaluations, can lead to significant gains in employee performance. This highlights the necessity for continuous professional development and the potential of AI in personalizing training approaches.

Verma, Tripathi, and Pant (2024) further contributed to the understanding of vision transformers by implementing them on the SPECT heart dataset [12]. Their comparative study demonstrated that transformers not only achieved higher segmentation accuracy but also provided better interpretability, making them a valuable tool in clinical settings.

Stenosis Detection Applications: Jungiewicz et al. (2023) explored the use of vision transformers for detecting stenosis in coronary arteries [13]. Their research illustrates the effectiveness of transformers in analyzing angiographic images, which is critical for early diagnosis and treatment of coronary artery disease. The study showcases how advanced imaging techniques can be enhanced through innovative machine learning applications.

Antimicrobial Properties and QSAR Investigations: Saluja (2024) investigated the antimicrobial properties of pyrazolone compounds alongside their quantitative structure activity relationship (QSAR) investigations [14]. This study contributes to the drug discovery field by demonstrating how computational models can predict the effectiveness of novel compounds. Such research not only informs the development of new antimicrobial agents but also underscores the role of technology in enhancing pharmaceutical research.

Predicting Mortality Risk from Health Records: Antikainen et al. (2023) expanded the application of transformers by utilizing them to predict mortality risk in cardiac patients based on heterogeneous electronic health records [15]. Their findings demonstrate the capability of transformer models to integrate diverse data sources, leading to improved predictive outcomes. This research highlights the potential of transformers in enhancing clinical decision-making processes.

Retrospective Insights on Vision Transformers: Parvaiz et al. (2023) provided a reflective overview of the use of vision transformers in medical computer vision [16]. They discussed the evolution of these models and their unique advantages in handling complex datasets. This retrospective analysis emphasizes the ongoing relevance of transformers in advancing medical diagnostics and patient care.

Advances in Medical Image Segmentation: Li et al. (2024) introduced the LViT model, which combines language processing capabilities with vision transformers to enhance medical image segmentation [17]. This innovative approach leverages the strengths of both modalities, allowing for more nuanced interpretations of medical images. The study demonstrates that integrating linguistic features can significantly im- prove segmentation accuracy, particularly in complex clinical scenarios.

Wang, Meng, and Wang (2023) explored the application of a vision-series transformer in screening for coronary heart diseases using coronary CT angiography [18]. Their findings indicate that the model effectively identifies critical features in imaging data, facilitating timely diagnosis. This work underscores the potential of transformers to enhance traditional imaging techniques, improving diagnostic workflows.

Enhancing Heart Disease Prediction: Rahman et al. (2024) focused on utilizing a self-attention-based transformer model to enhance heart disease prediction [19]. Their research illustrates the model's ability to capture intricate relationships within patient data, leading to more accurate risk assessments. This study emphasizes the transformative potential of transformers in predictive analytics, particularly in managing cardiovascular health.

Vaid et al. (2023) reported on the application of a foundational vision transformer to improve diagnostic performance for electrocardiograms (ECGs) [20]. Their results indicate that the transformer outperforms conventional methods, showcasing its efficacy in processing temporal data and detecting abnormalities. This advancement highlights the significance of adopting transformer models in real-time diagnostic settings.

The intersection of machine learning (ML) and vision transformer (ViT) technologies in cardiovascular health monitoring has led to significant advancements in diagnosis and prediction. This review summarizes key studies that explore the application of these methodologies in heart disease prediction, medical image analysis, and patient outcome forecasting. The literature reflects a dynamic landscape in which AI and ML are increasingly integrated into various domains, particularly healthcare and human resources. From enhancing disease detection methodologies to optimizing recruitment processes and improving employee training, these technologies hold transformative potential. As these fields continue to evolve, addressing ethical considerations and implementation challenges will be crucial for maximizing their benefits and fostering innovation.

## III. METHODOLOGY

- Dataset: Our study makes use of a large dataset of electrocardiogram (ECG) signals that spans a range of cardiovascular conditions and health states. The dataset in question comprises 929 ECG images that have been accurately categorized into four distinct groups, each of which offers important insights into cardiac health:
- ECG images of myocardial infarction patients: This subset consists of 240 images of individuals diagnosed with myocardial infarction (MI), also referred to as a heart at- tack. These pictures record the heart's electrical impulses both during and after a heart attack, giving important details regarding the acute cardiac defects connected to this illness.
- ECG Images for Patients with Normal Heartbeat: There are 233 images in this category that show people with a normal cardiac rhythm and a healthy circulatory system. These pictures provide as a reference point for cardiac health and aid in identifying abnormalities that point to cardiovascular conditions.
- ECG Images of Patients with a History of MI: 172 photos from patients who have previously experienced a myocardial infarction are included in this category. The long-term effects of MI on heart function may be revealed by the ECG signals acquired in these images, which may exhibit enduring abnormalities or proof of cardiac remodeling following a prior cardiac event.
- Normal Person ECG photos: 284 images from individuals without a history of heart disease or known cardiovascular anomalies are included in this group. These images show typical ECG patterns observed in healthy individuals and provide a standard against which images from patients with cardiovascular issues can be compared.

Vision Transformer (ViT) Model: A breakthrough in computer vision, the Vision Transformer (ViT) model offers a novel approach to the processing and analysis of visual data. ViT employs self-attention processes that are influenced by the Transformer architecture, which was initially developed for natural language processing applications, as opposed to conventional convolutional neural networks (CNNs), which rely on convolutional layers for feature extraction. ViT is able to effectively extract key features for classification and other subsequent tasks from photos and capture spatial correlations in images thanks to this innovative approach.

The Vision Transformer (ViT) model leverages self-attention to generate representations, allowing it to focus on different parts of the input image. The image is divided into smaller, non-overlapping patches, with each patch treated as a token in the self-attention mechanism. This enables the model to capture spatial dependencies across the entire image.

Patch Embedding: The input image is split into patches, and each patch is linearly embedded to create initial representations. These act as tokens for further processing, similar to how NLP models treat text.

Positional Encoding: To account for spatial relationships, positional encodings are added to the patch embeddings. These encodings help the model distinguish the relative or absolute positions of patches in the image.

Transformer Encoder: The core of ViT consists of multiple transformer encoder layers, which include self-attention and feedforward neural networks. The self-attention mechanism allows the model to focus on important patches, capturing long-range dependencies. The feedforward networks process the attended representations to extract higher-level features.

Classification Head: After processing through encoder layers, the final representation is passed through a classification head, typically consisting of fully connected layers, to predict the image's class.

ViT uses gradient descent and backpropagation for optimization. Its ability to handle input sequences of any length makes it versatile for tasks beyond image classification, such as object detection and segmentation.

## IV. IMPLEMENTATION

To create a flow for this study and ensure a seamless and precise comparison, we went into considerable depth regarding each step's execution, as demonstrated below:

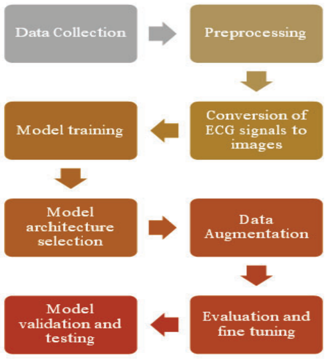


Fig. 1. Flow chat data collection

1) Data Collection: To build a successful CVD detection system using Vision Transformer (ViT) models, start by collecting a large dataset of ECG signals. To effectively reflect a diverse spectrum of cardiovascular illnesses, the collection must include both normal and pathological recordings. Access to a big and diverse dataset is crucial for rapidly training machine learning models and ensuring their ability to generalize to new data.

2) Preprocessing: After curating the dataset, standardize the ECG signals using preprocessing techniques. To ensure compatibility with the ViT model, a series of procedures are performed, including resampling, normalization, denoising, and segmentation. Resampling may be required to standardize the sampling rate of ECG signals, whilst normalization aids in scaling the signals to a regular range. Denoising techniques such as filtering and wavelet denoising are used to remove unnecessary noise from signals that can misrepresent the underlying cardiac data. Segmentation is critical for identifying individual heartbeats or segments within ECG signals, allowing for more accurate analysis and categorization.

3) Conversion of ECG Signals to Images: To employ the ViT model, pre- processed ECG signals must be translated into 2D or 3D image formats. This update allows the model to use its self-attention mechanism to efficiently assess spatial correlations in the ECG dataset. Time-domain or frequency-domain visualization techniques are commonly used to convert ECG signals into image-like representations, with each pixel representing a time-frequency datapoint.

These images capture the temporal and spectral characteristics of ECG signals, providing useful information for the ViT model to learn from.

4) Data Augmentation: Data augmentation procedures increase dataset diversity and robustness. These changes replicate differences in patient location, electrode positioning, and signal quality, all of which contribute to variability in real-world ECG recordings. Augmentation techniques such as rotation, scaling, flipping, and translation are employed to generate augmented samples, effectively expanding the dataset and improving the model's ability to generalize to previously unseen data.

5) Model Architecture Selection: Selecting the appropriate ViT model architecture is crucial for achieving optimal performance while balancing computational resources and model complexity. The model design is influenced by factors such as dataset size, available computational resources, and desired performance metrics. Smaller ViT models may be suitable for smaller datasets or with limited computational resources, but larger models with more parameters may be necessary to capture complex patterns in larger datasets.

6) Model Training: After deciding on a model architecture, divide the dataset into training, validation, and test sets. The ViT model is then trained on the training data using suitable loss functions, such as categorical cross-entropy for multi-class classification problems, as well as optimization techniques such as the Adam optimizer. During training, the model learns to extract useful information from ECG images and correctly forecast the presence of cardiovascular issues.

7) Evaluation and Fine-Tuning: After training, the model's performance on the validation set is assessed to establish its ability to detect cardiovascular issues. The model's performance is quantified using evaluation criteria such as sensitivity, specificity, accuracy, and an F1 score. Based on the evaluation results, the model can be fine tuned by adjusting hyperparameters or experimenting with different training processes to improve performance.

8) Model Validation and Testing: Following training and fine- tuning, the model is tested on an independent test set to ensure accurate performance estimates. The test set consists of previously unknown ECG data that was not presented to the model during training or validation. The model's sensitivity, specificity, accuracy, and other pertinent metrics are assessed to determine its effectiveness in CVD detection. Furthermore, the model's performance can be compared to existing diagnostic techniques or expert annotations to guarantee its clinical relevance and usefulness.

## V. RESULT AND ANALYSIS

The study employed a diverse set of pre-processed electro-cardiogram (ECG) signals from both normal and pathological records, which represented a wide spectrum of cardiovascular diseases. To guarantee that the dataset fit the requirements of the Vision Transformer (ViT) model, it was rigorously pre-processed, including normalization, denoising, and segmentation. This preprocessing was designed to standardize the data and uncover key properties required for effective model training. The dataset was then partitioned into different training and validation sets to aid in model evaluation and performance assessment.

The ViT-based classification model was then constructed and trained on the pre-processed dataset, employing the appropriate loss functions and optimization techniques. Throughout the training process, performance indicators such as loss and accuracy were monitored to evaluate the model's learning and generalization skills. The ViT-based algorithm performed well in classifying ECG images into various cardiovascular illnesses, indicating its potential as a dependable diagnostic tool for detecting cardiac anomalies.

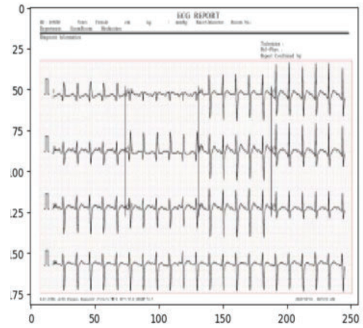


Fig. 2. Fig. 2.

Specifically, the algorithm proved extremely accurate in distinguishing between various cardiovascular illnesses, including myocardial infarction, irregular heartbeats, and normal heart rhythms. This capability displays the model's ability to recognize minor anomalies indicative of underlying heart problems, allowing for early detection and intervention. By using the capabilities of ViT-based deep learning techniques, the algorithm offers a viable avenue for improving the diagnostic accuracy and efficacy of cardiovascular disease detection, resulting in better patient care and outcomes.

The diagnostic accuracy of the Vision Transformer (ViT) based model was evaluated utilizing key performance metrics such as sensitivity, specificity, and AUC-ROC. The ViT model was extremely sensitive in detecting myocardial infarction and irregular heartbeats, both of which are significant indicators of cardiovascular disease. Furthermore, the specificity values revealed few false positives, indicating that the model can correctly distinguish between normal and pathological ECG patterns. The AUC-ROC scores verified the model's capacity to accurately distinguish between various cardiovascular illnesses, emphasizing its potential as a reliable diagnostic tool in clinical settings.

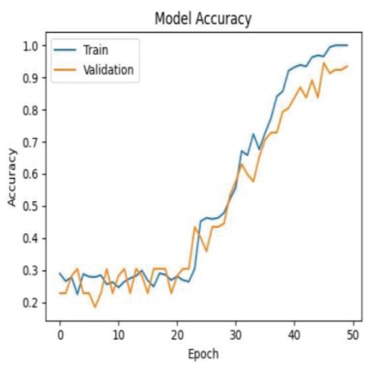


Fig. 3. Model accuracy

To contextualize the performance of the ViT-based model, it was compared to traditional machine learning approaches and cutting-edge deep learning models commonly employed in CVD detection tasks. These comparative evaluations revealed that the ViT model beat other approaches in terms of accuracy, sensitivity, and specificity. This superiority highlights the usefulness of self-attention processes exhibited in ViT architectures, which excel at capturing global dependencies and contextual information inside ECG images. The ViT based model surpasses earlier approaches, demonstrating its ability to transform CVD diagnosis by leveraging cutting-edge deep learning techniques to improve diagnostic accuracy and patient care outcomes.

The model loss, determined on a different validation set, is a critical metric in assessing the generalizability of the Vision Transformer (ViT) model. It calculates the difference between the model's predictions and the true labels on unseen ECG pictures, providing information on the model's performance on data it did not encounter during training. A decreased model loss illustrates the ViT model's ability to adapt learned patterns to new ECG pictures, indicating its usefulness in real-world scenarios.

Analysing patterns in both training and model loss over training and validation epochs provides valuable insights into the ViT model's training dynamics and ability to generalise to new data sets. Ideally, both training and model loss should drop steadily across epochs, indicating that the model is gradually learning relevant characteristics from the ECG data and improving performance. However, deviations from this ideal condition, such as a steady decline in training loss followed by a plateau or increase in model loss, may indicate overfitting. In such cases, the model may have memorised noise or quirks in the training data, rendering it unable to efficiently generalise to new samples.

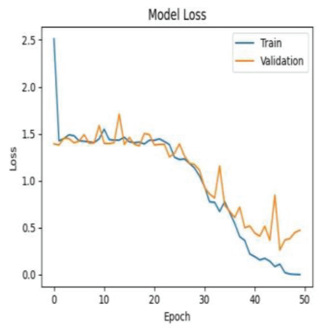


Fig. 4. Model loss

## VI. CONCLUSION

In the goal of revolutionizing cardiovascular health, the incorporation of cutting-edge ways to detecting cardiac diseases represents a significant advancement in the medical industry. This initiative aims to reinvent the landscape of cardiovascular care through the use of sophisticated technologies, creative techniques, and interdisciplinary collaboration.

The research has established the foundation for early diagnosis and personalized therapies in cardiovascular illnesses by meticulously utilising artificial intelligence, wearable de- vices, genetic screening, and improved imaging modalities. These innovative technologies provide healthcare professionals with precise risk assessment tools and patients with real-time monitoring capabilities, promoting a proactive approach to cardiovascular health management.

Furthermore, the project's emphasis on personalized medicine, which is informed by genetic screening and specific risk assessments, signifies a paradigm shift towards individualized treatment approaches. Healthcare professionals can personalize therapies to each patient's unique genetic composition, boosting therapy efficacy and patient outcomes. The incorporation of modern technology into cardiovascular health detection not only improves diagnostic accuracy, but also provides opportunities for preventive interventions and lifestyle changes. Real-time monitoring, predictive analytics, and environmental sensing help to provide a comprehensive understanding of cardiovascular health, allowing for timely interventions and proactive risk factor management.

To summaries, “Revolutionizing Cardiovascular Health: Cutting-Edge Approaches to Detecting Heart Conditions” represents a transformative perspective for cardiovascular care. This initiative aims to empower individuals, improve health- care results, and, eventually, change the norms of cardiovascular health management in the modern era through the use of innovation, personalized medicine, and data-driven techniques.

## REFERENCES


[1] A. Rath, D. Mishra, G. Panda, and S. C. Satapathy, “Heart disease detection using deep learning methods from imbalanced ECG samples,” Biomedical Signal Processing and Control, vol. 68. Elsevier BV, p. 102820, Jul. 2021. doi: 10.1016/j.bspc.2021.102820.

[2] C. Fan, Q. Su, Z. Xiao, H. Su, A. Hou, and B. Luan, “ViT-FRD: A Vision Transformer Model for Cardiac MRI Image Segmentation Based on Feature Recombination Distillation,” IEEE Access, vol. 11. Institute of Electrical and Electronics Engineers (IEEE), pp. 129763–129772,2023. doi: 10.1109/access.2023.3302522.

[3] S. Sengar and M. Pandey, “To Study the Effect of Job Satisfaction on the Performance of Academic Faculties Working in Private Colleges and Private Universities in Indore,” International Journal for Global Academic & Scientific Research, vol. 3, no. 1. International Consortium of Academic Professionals for Scientific Research, pp. 13–24, Apr. 04, 2024. doi: 10.55938/ijgasr.v3i1.69.

[4] H. Kim, M. Ishag, M. Piao, T. Kwon, and K. Ryu, “A Data Mining Approach for Cardiovascular Disease Diagnosis Using Heart Rate Variability and Images of Carotid Arteries,” Symmetry, vol. 8, no. 6. MDPI AG, p. 47, Jun. 13, 2016. doi: 10.3390/sym8060047.

[5] Q. Abbas, A. Hussain, and A. R. Baig, “Automatic Detection and Classification of Cardiovascular Disorders Using Phonocardiogram and Convolutional Vision Transformers,” Diagnostics, vol. 12, no. 12. MDPI AG, p. 3109, Dec. 09, 2022. doi: 10.3390/diagnostics12123109.

[6] M. R. Naidji and Z. Elberrichi, “A Novel Hybrid Vision Transformer CNN for COVID-19 Detection from ECG Images,” Computers, vol. 13, no. 5. MDPI AG, p. 109, Apr. 23, 2024. doi: 10.3390/computers13050109.

[7] S. Pratap Singh Rathore, “Analysing the efficacy of training strategies in enhancing productivity and advancement in profession: theoretical analysis in Indian context,” International Journal for Global Academic & Scientific Research, vol. 2, no. 2. International Consortium of Academic Professionals for Scientific Research, pp. 56–77, Jun. 30, 2023. doi: 10.55938/ijgasr.v2i2.49.

[8] T. P. Naidu et al., “A Hybridized Model for the Prediction of Heart Disease using ML Algorithms,” 2021 3rd International Confer- ence on Advances in Computing, Communication Control and Net- working (ICAC3N), Greater Noida, India, 2021, pp. 256-261, doi: 10.1109/ICAC3N53548.2021.9725780.

[9] K. Al-hammuri, F. Gebali, A. Kanan, and I. T. Chelvan, “Vision transformer architecture and applications in digital health: a tutorial and survey,” Visual Computing for Industry, Biomedicine, and Art, vol. 6, no. 1. Springer Science and Business Media LLC, Jul. 10, 2023. doi: 10.1186/s42492-023-00140-9.

[10] S. Granizo et al., “A Comparative Analysis of Vision Transformers and Convolutional Neural Networks in Cardiac Image Segmentation,” 2024 12th International Symposium on Digital Forensics and Security (ISDFS), vol. abs/2102.04306. IEEE, pp. 1–7, Apr. 29, 2024. doi: 10.1109/isdfs60797.2024.10527254.

[11] S. Pratap Singh Rathore, “The Impact of AI on Recruitment and Selection Processes: Analysing the role of AI in automating and enhancing recruitment and selection procedures,” International Journal for Global Academic & Scientific Research, vol. 2, no. 2. International Consortium of Academic Professionals for Scientific Research, pp. 78–93, Jun. 30, 2023. doi: 10.55938/ijgasr.v2i2.50.

[12] P. Verma, V. Tripathi, and B. Pant, “Implementation of Vision Transformers on SPECT Heart Dataset: A Comparative Study,” Lecture Notes in Networks and Systems. Springer Nature Singapore, pp. 119–127, 2024. doi: 10.1007/978-981-99-9521-9 10.

[13] M. Jungiewicz, P. Jastrzebski, P. Wawryka, K. Przystalski, K. Sabatowski, and S. Bartus´, “Vision Transformer in stenosis detection of coronary arteries,” Expert Systems with Applications, vol. 228. Elsevier BV, p. 120234, Oct. 2023. doi: 10.1016/j.eswa.2023.120234.

[14] V. Saluja, “Antimicrobial Properties Of Pyrazolone Compounds With Their Qsar Investigations,” International Journal for Global Academic & Scientific Research, vol. 3, no. 1. International Consortium of Academic Professionals for Scientific Research, pp. 25–35, Apr. 04, 2024. doi: 10.55938/ijgasr.v3i1.70.

[15] E. Antikainen et al., “Transformers for cardiac patient mortality risk prediction from heterogeneous electronic health records,” Scientific Reports, vol. 13, no. 1. Springer Science and Business Media LLC, Mar.02, 2023. doi: 10.1038/s41598-023-30657-1.

[16] A. Parvaiz, M. A. Khalid, R. Zafar, H. Ameer, M. Ali, and M. M. Fraz, “Vision Transformers in medical computer vision—A contemplative retrospection,” Engineering Applications of Artificial Intelligence, vol. 122. Elsevier BV, p. 106126, Jun. 2023. doi: 10.1016/j.engappai.2023.106126.

[17] Z. Li et al., ”LViT: Language Meets Vision Transformer in Medical Image Segmentation,” in IEEE Transactions on Medical Imaging, vol.43, no. 1, pp. 96-107, Jan. 2024, doi: 10.1109/TMI.2023.3291719.

[18] K. Wang, H. Meng, and X. Wang, “Application of Vision-Series Transformer in screening for coronary heart diseases using coronary CT angiography,” Proceedings of the 2023 4th International Conference on Computing, Networks and Internet of Things. ACM, pp. 421–425, May 26, 2023. doi: 10.1145/3603781.3603858.

[19] A. U. Rahman, Y. Alsenani, A. Zafar, K. Ullah, K. Rabie, and T. Shongwe, “Enhancing heart disease prediction using a self-attention based transformer model,” Scientific Reports, vol. 14, no. 1. Springer Science and Business Media LLC, Jan. 04, 2024. doi: 10.1038/s41598024-51184-7.

[20] A. Vaid et al., “A foundational vision transformer improves diagnostic performance for electrocardiograms,” npj Digital Medicine, vol. 6, no. 1 Springer Science and Business Media LLC, Jun. 06, 2023. doi:10.1038/s41746-023-00840-9.