AI-Driven Cardiovascular Risk Prediction in Athletes Using NLP and Large Language Models: A Comprehensive Review

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Abstract:

Cardiovascular diseases, or CVDs, still show up as one of the big health worries for athletes, mainly because of intense physical training, physiological strain, and those hidden cardiac irregularities that are not always obvious. Spotting cardiovascular risk early is crucial, because otherwise you can get serious outcomes like arrhythmias, myocardial problems, hypertension, and even sudden cardiac arrest. Lately, Artificial Intelligence, Natural Language Processing, and Large Language Models have basically reshaped how predictive healthcare is done, mostly by letting systems make sense of huge volumes of medical and physiological information in an intelligent way. In this review, we lay out a broad, no-rushed look at AI-based cardiovascular risk prediction systems that were built for athletes, using machine learning, deep learning, NLP, and transformer-style LLM architectures. This review also goes into how structured data and unstructured data can be combined, especially when you pull them from electronic health records, wearable sensors, IoT devices, ECG reports, clinical notes, and biomedical literature, so you can aim for more personalized cardiovascular evaluation. A bunch of AI approaches are taken apart and compared, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) systems, Random Forest, Support Vector Machines, and transformer-oriented frameworks like BERT, GPT, and BioBERT. These models are discussed in terms of disease prediction, risk leveling, and clinical decision assistance. There is also an emphasis on explainable AI, predictive analytics, and what you might call "smart" monitoring mechanisms, since these can improve diagnostic precision, support ongoing health surveillance, and strengthen athlete-specific health management. Beyond that, the review talks through the current problems, including data heterogeneity, the difficulty of interpreting models, computational overhead, privacy protection, and the practical challenge of real time clinical deployment. It also points out research gaps—multimodal health data blending, as well as more personalized sports medicine workflows. Overall, the results suggest that AI-driven healthcare

Keywords: *Artificial Intelligence (AI), Cardiovascular Risk Prediction, Natural Language Processing (NLP), Large Language Models (LLMs), Personalized Medicine, Athlete Healthcare Monitoring.*

I. INTRODUCTION

Cardiovascular diseases, CVDs, are among the most common causes of death and long-term health problems worldwide, influencing not only the general population but also professional athletes and people who stay physically active. Even if athletes are usually seen as fit and healthy, really intense training routines, prolonged physical effort, psychological pressure, and genetic predispositions can add to the chance of unseen heart issues like arrhythmias, hypertrophic cardiomyopathy, myocarditis, hypertension, and sudden cardiac arrest. Lately, there have been more reports of sudden cardiac death in athletes during training sessions or competitive moments, and this has pushed sports medicine to look for earlier cardiovascular risk checks and continuous health follow-up tools. Conventional diagnostics mainly rely on periodic clinical reviews, electrocardiograms ECG, echocardiography, and evaluations done by physicians, but these familiar methods often miss real-time monitoring, personalized healthcare insight, and early forecasting of cardiovascular complications [1].

The rapid advancement of Artificial Intelligence (AI) Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP) and Large Language Models (LLMs) has really been reshaping modern healthcare systems , letting them do disease anticipation, automated clinical review, and more tailor made medical choices. AI powered healthcare tools can sift through huge amounts of both structured and unstructured health data, with more speed and accuracy than the older, traditional systems. These tools are being put into cardiovascular healthcare use cases more and more often, for diagnosis, risk grading , predictive analytics, clinical decision support, and also remote patient observation. In sports medicine , AI based predictive platforms can keep tracking athletes physiological signals continuously and flag unusual cardiovascular patterns early, before serious complications show up. Machine Learning techniques like Support Vector Machines, Random Forests, Decision Trees, Gradient Boosting Machines, and K-Nearest Neighbor have been used a lot for cardiovascular disease prediction, and healthcare analytics. In practice these models can take in healthcare datasets, find less obvious associations and then estimate risk based on patient history, lab results, wearable sensor readings, and routine clinical documentation. Also deep learning methods such as Convolutional Neural Networks, Recurrent Neural Networks, Long Short-Term Memory networks [2], Autoencoders, and hybrid CNN-LSTM setups have shown strong outcomes for things like medical image analysis, ECG signal interpretation, disease labeling, and sequential healthcare data study. Overall, deep learning approaches are very good at pulling out intricate spatial-temporal cues from big biomedical collections, which then tends to raise prediction accuracy and increase the efficiency of disease detection.

Alongside ML and DL technologies, Natural Language Processing has turned into an essential bit of intelligent healthcare systems. NLP methods let computers decipher, process, and examine human language found in clinical notes, discharge summaries, electronic health records (EHRs), biomedical literature, physician observations and diagnostic reports. Since much of the healthcare info sits in unstructured text form, NLP powered systems assist in pulling out useful clinical signals that bolster disease prediction, as well as healthcare analytics. For cardiovascular healthcare, NLP is used for symptom extraction, automated report inspection, clinical text mining, medical question answering, patient surveillance, and predictive healthcare modeling. When NLP blends with healthcare analytics, clinicians can recognize cardiovascular risk factors more sharply and improve patient management strategies [3]. Recently, Large Language Models like BERT, GPT, BioBERT, RoBERTa and Med-PaLM have shown up as really capable AI technologies that can read and also craft human language, with strong contextual accuracy. These transformer based architectures have improved healthcare text mining, clinical note writing, medical summarization, and more adaptive decision support functions. With LLMs it becomes possible to ingest huge collections of medical literature, clinical stories, patient backgrounds, and biomedical datasets, then return useful signals and more tailored healthcare suggestions.

In cardiovascular care specifically, LLMs help with automated diagnosis, risk forecasting, illness trend prediction, plus patient focused therapy planning. And because they can blend multimodal healthcare inputs, they fit well for athlete centered cardiovascular monitoring systems, and for intelligent sports medicine applications [4]. The increasing popularity of wearable healthcare instruments and Internet of Things (IoT) based monitoring setups has made AI-driven predictive healthcare frameworks even stronger. Wearable gadgets like smartwatches, ECG monitors, biosensors, and fitness trackers keep gathering physiological data non-stop, such as heart rate, blood pressure, oxygen saturation, sleep quality, respiration rate, and also physical activity levels. AI methods built into these wearables can interpret the incoming signals in real time and send early alerts about cardiovascular issues. In practice, these tools matter a lot for preventive healthcare, athlete performance tuning, recovery tracking, and tailored treatment plans. Also, IoT powered medical systems support continuous remote supervision, cloud based analytics, and automated clinical assistance, which helps expand healthcare access and supports faster real time choices. Personalized medicine has become this important research direction in sports healthcare, because it keeps attention on individualized diagnosis and treatment, plus disease prevention methods that are built around genetic, physiological, behavioral, and environmental traits [5]. AI driven personalized healthcare systems do that by reading athlete specific medical histories, genomic information, wearable sensor signals, and clinical timelines, then they output customized healthcare guidance. In the same way, personalized cardiovascular risk prediction frameworks can support physicians, sports scientists and other healthcare professionals in building training schedules that are better matched, nutrition approaches, recovery rhythms, and preventive interventions that match each athlete. These more intelligent healthcare systems end up strengthening athlete safety, boosting performance, and improving long term cardiovascular health control, especially when decisions are made early.

Even with substantial advancements in AI driven healthcare tech, there are still several obstacles in cardiovascular risk prediction systems. One big snag is the heterogeneity of healthcare data that comes from many places, like EHRs , wearable devices, clinical reports, genomic databases and sensor networks. You get data inconsistency, missing values, noise, privacy concerns, and limited interoperability, and all of this reduces how reliable the predictive healthcare system can be. On top of that, many AI and deep learning models have limited explainability, so clinical interpretation becomes difficult for healthcare professionals. There is also the computational burden of large scale healthcare analytics plus the real time execution difficulties, which further restrict the actual rollout of intelligent healthcare systems in sports medicine settings. Beyond that, ethical topics tied to patient privacy, data security, algorithmic bias, and the responsible use of AI continue to be key research points [6]. This comprehensive review focuses on how AI based cardiovascular risk prediction works for athletes, particularly when NLP and Large Language Models are used. It goes into the use of Artificial Intelligence, Machine Learning, deep learning, Natural Language Processing, transformer driven LLMs, wearable hardware, and IoT systems within smarter cardiovascular healthcare programs. The paper also looks at what's been happening recently for disease forecasting, personalized medicine, and athlete specific monitoring setups, plus explainable AI frameworks, and predictive healthcare analytics that can be more clinically helpful. In the background it critically considers existing research roadblocks, the limits we still have, and what future directions might look like, when building reliable scalable and interpretable AI for sports medicine needs [7]. Overall, when intelligent technologies connect with tailored healthcare strategies, the next wave of cardiovascular prediction systems can improve athlete safety, prevention of disease, clinical choices, and longer term healthcare management.

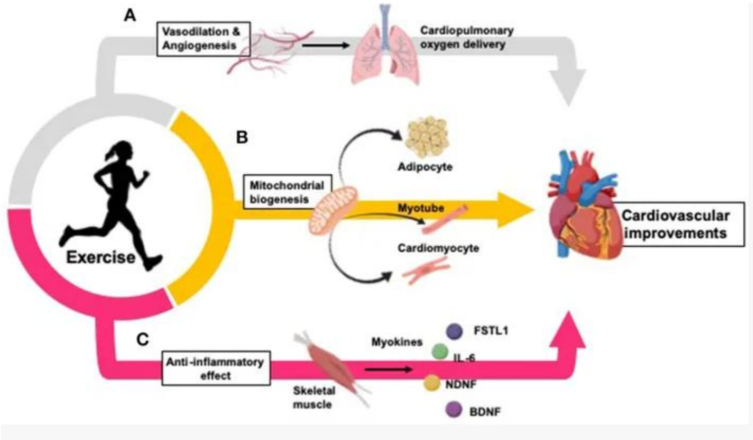

Figure 1: Exercise-Induced Cardiovascular Adaptations [5]

This figure 1 illustrates how regular exercise improves cardiovascular health through vasodilation, angiogenesis, mitochondrial biogenesis, and anti-inflammatory myokine release, ultimately enhancing cardiopulmonary oxygen delivery and overall heart function.

II. MACHINE LEARNING IN CARDIOVASCULAR PREDICTION

Machine Learning (ML) has been growing into one of the most noticeable technologies in modern healthcare systems, helping with disease prediction, clinical diagnosis, and a more intelligent kind of decision-making. In the heart and vascular space, these machine learning methods are now used more and more to dig up hidden disease patterns, to make sense of complicated medical datasets, and to guess cardiovascular risks much earlier than before. Cardiovascular diseases (CVDs) like hypertension, arrhythmias, coronary artery disease, myocardial infarction, heart failure, and sudden cardiac arrest still count among the main causes of death worldwide. In athletes, these conditions can stay unseen, because of intense physical activity, plus the physiological adaptations that come with sports training. Because of that, doing early cardiovascular risk forecasting with machine learning models becomes critical, for athlete safety, preventive medicine efforts, and long term performance planning.

Traditional cardiovascular diagnosis still mostly relies on the physician's own experience, plus lab investigations, ECG analysis, imaging systems, and the manual sifting through patient records. Even though these methods remain clinically helpful, they often have trouble with huge healthcare databases, and they don't usually deliver true real time predictive cues [8]. Machine learning helps with these gaps since it can learn useful relationships from both structured and unstructured healthcare data without much hand crafting. ML methods may process patient demographics, medical background, physiological waveforms, wearable sensor readings, habits and daily routine details, lab results, and electronic health records EHRs, and then forecast cardiovascular issues with better accuracy while using less time. That's why machine learning is now a key piece inside smarter healthcare systems and personalized medicine frameworks, where clinicians can react quicker, and treatment planning can become more tailored. Machine learning techniques used for cardiovascular prediction are usually sorted into supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning approaches. Out of those, supervised learning methods get used the most, because they rely on labeled healthcare datasets, to teach predictive models. You will often see Support Vector Machines (SVM), Decision Trees (DT), Random Forest (RF), Logistic Regression (LR), Naïve Bayes (NB), Gradient Boosting Machines (GBM), and K-Nearest Neighbor (KNN) in practical workflows [9]. These methods help with patient state classification, disease likelihood estimation, and cardiovascular risk assessment, by spotting associations between medical variables and physiological signs.

Logistic Regression is among the earliest machine learning methods used in cardiovascular disease prediction, mainly because its structure is simple and the results feel explainable. It forecasts the probability of illness showing up, by using statistical linkages between independent clinical variables and the dependent outcome. In practice, Logistic Regression is frequently used for hypertension prediction, heart disease categorization, and in cardiovascular risk scoring systems as well. Even if the model gives results you can interpret, its ability to predict gets weaker when the healthcare data is highly nonlinear and when physiological connections are more intricate. Support Vector Machines have been getting a lot of attention in cardiovascular healthcare, not just because they can manage high-dimensional medical data, but also because they deal pretty well with nonlinear class assignments. In essence, SVM algorithms build an "optimal dividing plane" so that distinct disease categories can be separated [10]. In many cardiovascular prediction setups, SVM models show up for arrhythmia detection, ECG signal classification, heart disease diagnosis, and also for patient risk stratification. Their strong generalization ability helps raise classification accuracy, in particular when the amount of available healthcare data is limited. At the same time, SVM models can demand heavy computation, and they often need careful tuning of parameters, especially when large-scale clinical datasets are used. Decision Tree algorithms are widely used in intelligent healthcare systems, because they produce decision rules that are easy to read, for disease prediction. In practice these models divide healthcare data into hierarchical decision nodes using clinical features, like age, cholesterol levels, blood pressure, heart rate, smoking habits, and ECG patterns. Decision Trees also help with transparent and explainable cardiovascular risk assessment, that makes them a good fit for clinical decision support systems. Still, a single Decision Tree can end up with overfitting problems, and weaker prediction steadiness when the dataset is complicated. [11]

Random Forest, an ensemble learning approach rooted in multiple Decision Trees, has shown strong performance in tasks for cardiovascular disease forecasting. The Random Forest models merge the outputs from many trees to push up classification accuracy, steadiness, and overall generalization ability, not just one single tree doing everything. Because of how they operate, these models can deal well with missing healthcare records, messy clinical inputs, and large biomedical feature spaces. In practice, Random Forest algorithms are frequently applied for heart disease detection, cardiovascular event anticipation, wearable healthcare analytics, and athlete monitoring setups. Also, their ability to order feature relevance helps healthcare professionals pinpoint meaningful cardiovascular risk factors. K-Nearest Neighbor is another commonly used machine learning technique for cardiovascular forecasting. KNN, it classifies patient conditions by comparing likeness measures with nearby healthcare records. The idea is easy to implement, and it tends to work well on smaller medical datasets. Yet KNN models can become computationally costly, especially when the healthcare database gets huge, or when the clinical data is multidimensional [12]. On top of that, the final performance depends a lot on choosing the right distance metric and the use of feature normalization methods.

Naïve Bayes algorithms are probabilistic machine learning models that attempt to work out disease probability, based on Bayes' theorem. They can be quite useful in medical diagnosis settings, especially when healthcare information is uncertain, or incomplete in some way. Within cardiovascular healthcare systems, Naïve Bayes classifiers are often applied for disease prediction , patient categorization and even clinical text analysis. One big advantage is how fast the computation runs, plus the training effort is low, and they also fit real time healthcare apps reasonably well. Still, there is a drawback, the model assumes feature independence which can weaken prediction accuracy when biomedical variables are tightly correlated. Overall, machine learning has reshaped cardiovascular disease prediction, enabling smart healthcare analytics, automatic diagnosis, tailored medicine, and forecasting monitoring systems. ML approaches give efficient ways to work with huge biomedical data, find cardiac or vascular problems, and back preventive healthcare initiatives. When machine learning blends with wearable devices, IoT setups, language processing frameworks, and more advanced healthcare analytics, the prediction performance keeps getting better, including athlete focused health oversight . As these intelligent healthcare tools keep evolving, machine learning is likely to become even more central in next generation cardiovascular forecasting systems and precision sports medicine use cases [13].

III. DEEP LEARNING TECHNIQUES FOR DISEASE DETECTION

Deep Learning (DL) has shown up as a rather revolutionary branch of Artificial Intelligence (AI) that boosts disease detection, medical image analysis, predictive healthcare analytics, and even more intelligent clinical decision making. In contrast to older machine learning approaches which usually depend on heavy manual feature extraction, deep learning models learn stacked, layered feature representations by themselves, using huge healthcare datasets. In the cardiovascular healthcare area, DL techniques are often used to catch multiple heart conditions, for example heart diseases, rhythm disturbances, myocardial infarction, hypertension, heart failure, and other related vascular abnormalities, with strong diagnostic precision. These systems become extra useful in sports medicine and athlete healthcare, where continuous cardiovascular monitoring and early disease identification matter a lot, to help prevent serious complications like sudden cardiac arrest and cardiac dysfunction. Deep learning models get their inspiration from the structure and how the human brain functions, but they're implemented through artificial neural networks made of several hidden layers. In practice these networks learn spatial temporal, and also contextual relationships between biomedical signals and features. So, they can deal with complicated healthcare data by extracting patterns, like when different cues appear across time or in a specific clinical setting. Deep learning systems can also take on huge collections of both structured and unstructured medical records, including electrocardiograms (ECG), echocardiograms, scans from cardiac imaging, outputs from wearable sensors, electronic health records (EHRs), genomic information, and even physiological monitoring streams. Because of this, deep learning has turned into one of the most powerful technologies for predicting cardiovascular disease with intelligence and for driving healthcare automation [14]. Among a bunch of deep learning architectures, Convolutional Neural Networks, or CNNs, are some of the most often used models for disease detection and medical image analysis. They are built to automatically pull out spatial properties from raw input, via convolutional layers, pooling layers, activation steps, and then fully connected layers. In cardiovascular healthcare, CNNs get used a lot for ECG signal classification, arrhythmia detection, cardiac MRI interpretation, echocardiography assessment, and heart disease diagnosis. CNN based systems can also spot tiny irregularities inside cardiac signals and imaging collections, things that may not stand out during manual clinical review. And because they handle high dimensional biomedical data so well, they fit automated cardiovascular screening tasks plus athlete monitoring use cases. A pretty standard convolutional neural network, CNN, setup is made of convolution layers that pick up both low-level cues and higher-level features, then pooling layers that calm down the dimensionality, and afterward dense layers that end up doing the actual classification. The convolution step is useful for highlighting meaningful cardiovascular patterns including irregular heartbeat traces, odd looking signal shapes, and also structural heart anomalies. In practice, CNN models have shown clear strength at finding atrial fibrillation, ventricular rhythm disorders, ischemic heart disease, and even myocardial infarction, all from ECG readings. Additionally, transfer learning approaches that rely on pretrained CNN blueprints like ResNet, VGGNet, DenseNet, and InceptionNet have pushed up detection performance while keeping training less tangled and reducing computational demands [15].

Recurrent Neural Networks (RNNs) are another big category of deep learning models used for sequential healthcare data analysis, I mean they're used a lot in practice. Unlike CNNs, RNNs are made to handle temporal and time series information by keeping internal hidden memory states. In cardiovascular monitoring, these systems often produce ordered physiological signals like ECG waveforms, heart rate variability traces, respiration rhythms, and wearable sensor data streams. RNNs then try to learn how these signals relate over time so they can predict cardiovascular abnormalities and longer term patient health conditions. Still, standard RNNs run into gradient vanishing issues and they also struggle with long range dependency problems when the sequences get really long. To get around these limitations, Long Short-Term Memory LSTM networks were brought in as improved RNN architectures, able to learn long-range dependencies inside healthcare sequences. In practice, LSTM models have memory cells, plus input gates, forget gates, and also output gates, which kind of control what information moves through the model [16]. For cardiovascular healthcare, LSTM methods get used a lot for things like heart disease prediction, arrhythmia classification, ECG signal interpretation, blood pressure forecasting, and ongoing patient monitoring over time. Because they can hold onto temporal links across steps, they are pretty effective for real time athlete monitoring setups and for wearable healthcare applications.

Hybrid deep learning architectures that mix CNN and LSTM models have been getting a lot of attention in disease detection research lately. The CNN-LSTM frameworks blend the spatial feature extraction strength of CNNs with the temporal sequence learning ability of LSTMs. With these hybrids you can reach very high performance for cardiovascular disease prediction because the model looks at both the shape-like characteristics and the evolving, time related cues in biomedical signals, rather than just one side of the evidence. For instance, CNN layers may pull out ECG waveform details while LSTM layers track time dependent cardiac patterns, then use them for disease classification. Because of that, these combined architectures are being placed more often in intelligent healthcare systems, including athlete focused cardiovascular monitoring and predictive health analytics. Autoencoders are, another important deep learning method used across healthcare analytics, and anomaly detection too. They are unsupervised neural networks that aim to capture a compressed representation of healthcare information by encoding it first, then reconstructing the original input signal [17]. For cardiovascular work, autoencoders help spot irregular cardiac signals, reveal latent disease patterns, shrink data dimensionality, and also strip away noise in biomedical datasets. Variational Autoencoders, often written as VAEs and sparse autoencoders, are especially handy for medical feature discovery, and for disease classification problems where labeled healthcare data is limited.

Deep Belief Networks (DBNs) and Deep Neural Networks (DNNs) are also frequently used in intelligent cardiovascular healthcare systems. DNNs are made up of several fully connected hidden layers, where they can learn complicated nonlinear connections across healthcare features. In practice, they get employed for disease classification , cardiovascular risk scoring , and predictive healthcare analytics. DBNs, meanwhile, are built by stacking a set of Restricted Boltzmann Machines (RBMs) together, which helps them carry out unsupervised feature learning and craft a useful healthcare data representation. Even though these approaches have looked promising, they often demand big computational power, plus training sets that are quite extensive. Cardiac MRI, CT scans, ultrasound imaging, and echocardiography each produce very detailed biomedical images, and those still need careful interpretation for disease diagnosis. Convolutional neural network based systems can automatically break up heart structures, highlight disordered regions, catch plaque build up, and label cardiovascular conditions using imaging datasets. Automated visual analysis reduces the clinician workload, and it tends to raise the accuracy of clinical decisions. For athletes, these systems are useful for spotting concealed structural irregularities that could raise cardiovascular risks during demanding sports sessions [18].

IV. NLP AND LLM-BASED HEALTHCARE SYSTEMS

Natural Language Processing (NLP) along with Large Language Models (LLMs) have become really relevant in today's intelligent healthcare setups. Basically these tools help a computer to read, process, interpret, and later create human language, using huge amounts of healthcare records. In the cardiovascular field, NLP and systems powered by LLMs are now used more and more for things like illness forecasting, clinical guidance, parsing medical reports, continuous patient surveillance, and more tailored healthcare planning. And because a big portion of the medical evidence lives inside unstructured text formats, for example physician notes, discharge summaries, lab results, electronic health records (EHRs), prescriptions, and also biomedical literature, NLP methods take those messy documents and turn them into clearer clinical signals [19]. Traditional healthcare systems often have trouble analyzing unstructured clinical data quickly, because manual interpretation takes a lot of time and usually needs a high level of medical expertise. NLP techniques help with these limitations since they can pull out key medical entities, symptoms, disease patterns, treatment details and patient background automatically, almost without the same overhead. In cardiovascular healthcare, NLP applications are used for heart disease prediction, pulling out symptoms, interpreting ECG reports, classifying medical text, offering automated diagnostic assistance, and running intelligent healthcare analytics. With NLP-driven workflows, cardiovascular risk factors like hypertension, chest pain, irregular heartbeat, obesity, diabetes, smoking history, and genetic disorders can be detected from clinical narratives and routine healthcare documentation. Machine learning and deep learning based NLP approaches have definitely improved healthcare text analysis, and it helps a lot more than people first expected. Methods like tokenization, named entity recognition, sentiment analysis, text classification, and semantic comprehension give room for intelligent healthcare applications. In practice, deep learning models such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and transformer architectures have strengthened how healthcare systems process medical language, with strong context awareness. Altogether these tools make it easier to run automated clinical documentation, healthcare chatbot services, predictive analytics, and more patient centered healthcare experiences [20].

Large Language Models, such as BERT, BioBERT, GPT, RoBERTa, Med-PaLM, and ClinicalBERT, are advanced transformer based AI systems that can interpret tricky medical language and generate context aware healthcare information. Usually these models are trained on massive biomedical and healthcare datasets, so they can read, clinical records biomedical papers, notes from physicians, and patient narratives in a reliable way. For cardiovascular healthcare, LLMs help with disease forecasting, risk scoring, individualized treatment design, and more smart clinical decision support tools. Also their capacity to handle structured as well as unstructured healthcare signals makes them especially useful for personalized medicine efforts. NLP and LLM based healthcare systems are connected with wearable tech and IoT healthcare devices , so that continuous patient monitoring can happen [21]. For athlete healthcare, NLP driven analytics is used to digest health records, wearable sensor outputs and physician feedback, then it helps spot early cardiovascular risk clues before things escalate. Also there are intelligent conversational healthcare assistants that use LLM power , they give real time medical guidance, symptom checks, medication reminders and preventive wellness suggestions. All of that improves healthcare accessibility , increases patient participation, and supports remote healthcare oversight.

V. PERSONALIZED MEDICINE AND ATHLETE MONITORING

Personalized medicine has come up as a transformative path in modern healthcare, it really aims at individualized disease prevention, diagnosis, and a careful treatment plan along with ongoing patient management. Compared to older, more generalized healthcare models that tend to use the same kind of therapy across people, personalized medicine looks at how each person works in a more detailed way. It takes into account individual physiology, genetic profile(s), everyday lifestyle behaviors, surrounding environmental conditions, and even the medical history, then turns that into a tailored healthcare solution. In the context of cardiovascular healthcare, this approach helps a lot with pinpointing athlete-specific cardiovascular risks and it improves preventive healthcare management. When you add the integration of Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), wearable technologies, plus Internet of Things (IoT) systems, the whole cardiovascular monitoring process becomes much more powerful for athletes, and it supports a more personalized monitoring routine. Athletes go through intense physical conditioning, prolonged exertion, mental pressure, and biological adjustments that can raise the likelihood of unseen heart complications like rhythm irregularities, elevated blood pressure, heart muscle problems,[22] and sudden cardiac arrest. Because of this, nonstop cardiovascular observation is really necessary for protecting athlete wellbeing while also improving performance goals. AI based individualized healthcare setups evaluate athlete specific clinical history, ECG traces from screening sessions, output from wearable sensing devices, lab results, and training metrics to flag possible cardiovascular issues early. These smart health platforms help with early avoidance of disease and tailored medical actions that fit each person.

Wearable healthcare technologies have become one of the most important pieces in athlete monitoring systems. Devices like smartwatches, ECG monitors, fitness trackers, biosensors, and portable medical devices continuously collect physiological measures such as heart rate, blood pressure, oxygen saturation, respiration frequency, body temperature, sleep quality, and physical activity levels. AI plus deep learning algorithms sift through these real time health data streams, to notice unusual cardiac shapes, keep track of fatigue states, gauge recovery conditions, and flag cardiovascular threats. With steady monitoring, coaches, physicians, and sports scientists can make more informed calls about training intensity, rehabilitation routines, and medical interventions. Machine learning models like Random Forest, Support Vector Machines, Decision Trees, and also deep learning architectures that include CNNs and LSTMs are widely used to do athlete-specific cardiovascular prediction and monitoring [23]. In practice these systems find hidden disease signals , and they also examine time-based healthcare recordings in order to produce personalized care guidance. AI-driven setups can estimate overtraining situations, stress-linked cardiovascular irregularities, and performance decline by relying on past healthcare records and the usual physiological monitoring patterns. Genetic profiling helps surface inherited cardiovascular disorders and those athlete-linked risk signals tied to cardiac dysfunction. AI driven predictive analytics then blend genetic information with physiological monitoring data , aiming to craft tailored healthcare plans and preventive interventions. With these methods, early disease recognition gets a boost and long-term cardiovascular health management in sports medicine improves. In addition to predictive monitoring, AI based healthcare systems can help with intelligent rehabilitation and recovery control for athletes. These personalized platforms give individualized exercise directions, meal planning guidance, stress relief methods, and recovery roadmaps, based on athlete physiological reactions and current healthcare conditions, sometimes even when the situation changes fast.[24] Explainable AI methods also boost clinical transparency, because clinicians can see why a prediction happened, and how a treatment recommendation was formed, instead of just trusting a black box. Even with major improvements, personalized medicine and athlete monitoring systems still run into hurdles about healthcare data privacy, wearable sensor reliability problems, computational complexity, interoperability issues, and not enough clinical validation. Table 1 presents a comparative analysis of AI, NLP, and LLM-based healthcare systems used for cardiovascular disease prediction, intelligent monitoring, personalized medicine, and clinical decision support applications.

Table 1: Comparative Analysis of AI, NLP, and LLM-Based Healthcare Systems for Cardiovascular Prediction

Ref	Method/Technique	Key Findings	Limitations
[11]	Large Language Models (LLMs)	Improved medical text analysis and clinical decision support	Risk of hallucination and biased outputs
[12]	Conversational AI and GPT models	Enhanced maternal and newborn healthcare interaction	Ethical and privacy concerns
[13]	LLMs and predictive analytics	Improved prognostic prediction in heart failure patients	Limited pilot-scale validation
[14]	AI-enabled healthcare monitoring tools	Increased physical activity and patient engagement	Limited long-term clinical studies
[15]	AI healthcare analytics	Enhanced obesity prevention and personalized therapy	Requires continuous patient monitoring
[16]	Medical Large Language Models	Evaluated effectiveness of healthcare LLM systems	Benchmark datasets may not reflect real-world healthcare
[17]	Generative AI and explainable healthcare systems	Improved personalized and explainable healthcare services	High computational complexity
[18]	AI-integrated healthcare platform	Enhanced medical data management and patient monitoring	Data privacy and interoperability challenges
[19]	ML and DL algorithms	Improved healthcare analytics and disease prediction	Requires large-scale annotated datasets
[20]	AI and predictive analytics	Enhanced cardiovascular risk assessment and disease prediction	Limited real-time deployment
[21]	Explainable AI and ML	Improved transparency and precision in cardiovascular prediction	Limited real-world implementation
[22]	Machine Learning and AI	Enhanced predictive analytics and personalized treatment	Dependence on large healthcare datasets
[23]	Explainable AI and predictive analytics	Improved monitoring of heart failure patients	Limited disease-specific validation
[24]	EHR-integrated AI systems	Enhanced clinical decision support and patient monitoring	Privacy and interoperability issues
[25]	Machine learning algorithms	Improved early diagnosis	

VI. CONCLUSION AND FUTURE WORK

In this review, the role of Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), and Large Language Models (LLMs) in cardiovascular risk prediction and athlete healthcare monitoring has been pretty thoroughly examined. The study underscored how intelligent healthcare systems are shifting cardiovascular disease detection, predictive analytics, customized treatment plans, and even the clinical decision-making pipeline . AI driven predictive models, wearable healthcare technologies, IoT based monitoring systems, and transformer style LLM architectures have shown clear gains in early disease recognition, ongoing patient observation , and athlete specific healthcare oversight. Machine learning and deep learning methods like CNNs, RNNs, LSTMs, Random Forest, and Support Vector Machines have proven efficient for interpreting ECG traces, medical imaging, physiological signals, and healthcare documentation in support of cardiovascular disease prediction. The review also brought up how important NLP and LLM based healthcare systems really are, for pulling out useful clinical signals from messy unstructured sources. That means electronic health records, physician notes , and biomedical literature. There are personalized medicine setups that rely on AI together with wearable devices, which allow more tailored healthcare guidance, preventive action plans, and even a better approach to athlete performance management. Still , even with these gains, there are hurdles that keep showing up: concerns about healthcare data privacy, limited explainability in AI models, computational complexity, interoperability problems, and the missing proof from big real world clinical trials. Future research should lean into explainable plus interpretable AI systems so the clinical decisions stay transparent and understandable, not just opaque. There is room for improvement when multimodal healthcare data gets combined with federated learning, edge AI, and secure cloud based healthcare platforms, this could help boost predictive accuracy, and also strengthen real-time monitoring abilities.

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