ISSN: 2454-9940

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

E-Mail :
editor.ijasem@gmail.com
editor@ijasem.org

www.ijasem.org

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940

www.ijsem.org

Vol 18, Issue.2 May 2024

CARDIOVASCULAR DISEASE PREDICTION USING DEEP LEARNING, DQN AND DRL MODELS

C.SARAVANAN, G.SAIRAM, I.VAMSI KRISHNA, U.LAVAKUMAR

ABSTRACT

Cardiovascular diseases (CVDs) remain a leading cause of mortality worldwide, emphasizing the critical need for effective early detection and prevention strategies. In recent years, deep learning techniques have shown remarkable promise in various medical applications, including disease predict the risk of cardiovascular diseases using deep learning algorithms. Cardio Care utilizes a comprehensive dataset containing various demographic, clinical and lifestyle factors to train its predictive models. Leveraging deep learning architectures such as convolutional neural network and recurrent neural networks, CardioCare learns intricate patterns and relationships within the data to accurately predict the likelihood of an individual developing cardiovascular diseases over a specified timeframe. The mobile app provides users with an intuitive interface to input their relevant health information, including age, gender, blood pressure, cholesterol levels, smoking habits, and family history of CVDs. Upon submission CardioCare processes the data through its trained deep learning models and generates a personalized risk assessment report for the user. The development of Cardiocare aims to empower individuals with valuable insights into their cardiovascular health enabling proactive measures to mitigate risk factors and improve overall wellbeing.

INTRODUCTION

Insomnia is a common sleep disorder in which patients cannot sleep properly. Accurate detection of insomnia disorder is a crucial step for mental disease analysis in the early stages. The disruption in getting quality sleep is one of the big sources of cardiovascular syndromes such as blood pressure and stroke. The traditional insomnia detection methods are time-consuming, cumbersome, and more expensive because they demand a long time from a trained neurophysiologist, and they are prone to human error, hence, the accuracy of diagnosis gets compromised [1]. This paper proposes a novel phonography-based method for Fetal Breathing Movement (FBM) detection by its excitation sounds. It requires significantly less effort than the current procedures, and it allows long-term measurement, even at home. More than 50 pregnancies in the third trimester were examined, for a minimum of 20 minutes, taking synchronous long-term measurements using a commercial phonocardiographic fetal monitor and a 3D ultrasound machine [2].

Motion pattern analysis uses a variety of methods to recognise physical activities recorded by wearable sensors, video-cameras, and global navigation satellite systems. This paper presents motion analysis during cycling, using data from a heart rate monitor, accelerometric signals recorded by a navigation system, and the sensors of a mobile phone. Real cycling experiments were recorded in a hilly area with routes of about 12 km long [3]. Cardio Vascular Diseases (CVD) is the leading cause of death globally and is increasing at an alarming rate, according to the American Heart Associations Heart Attack and Stroke Statistics2021. This increase has been further exacerbated because of the current coronavirus (COVID-19) pandemic, thereby increasing the pressure on existing healthcare resources. Smart and Connected Health (SCH) is a viable solution for the prevalent healthcare challenges [4].

The alarmingly high mortality rate and increasing global prevalence of cardiovascular diseases (CVDs) signify the crucial need for early detection schemes. Phonocardiogram (PCG) signals have been historically applied in this domain owing to its simplicity and cost-effectiveness. In this article, we propose CardioXNet, a novel lightweight end-to-end CRNN architecture for automatic detection of five classes of cardiac auscultation namely normal, aortic stenosis, mitral stenosis, mitral regurgitation and mitral valve prolapse using raw PCG signa [5]. In low and middle income countries, infectious diseases continue to have a significant impact, particularly amongst the poorest in society. Tetanus and hand foot and mouth disease (HFMD) are two such diseases and, in both, death is associated with autonomic nervous system dysfunction (ANSD). Currently, photoplethysmogram or electrocardiogram monitoring is used to detect deterioration in these patients, however expensive clinical monitors are often required [6].

Heart Failure (HF) diagnosis, subsequent admissions, and possible readmissions present challenges for health systems worldwide. An increasing number of patients within an ageing population are surviving cardiac conditions which can leave them with residual heart function impairment. Follow-up visits of either confirmed HF sufferers or HF high-risk patients could be reduced through the implementation of Point-of-Care (PoC) measurement of N-terminal pro-B-type natriuretic peptide (NT-proBNP), an inactive signal portion of the active hormone BNP that is released in response to cardiac wall stretch [7]. Cardiovascular diseases currently pose the highest threat to human health around the world. Proper investigation of the abnormalities in heart sounds is known to provide vital clinical information that can assist in the diagnosis and management of cardiac conditions [8].

We present a smartphone-only solution for the detection of atrial fibrillation (AFib), which utilizes the built-in accelerometer and gyroscope sensors [inertial measurement unit, (IMU)] in the detection. Depending on the patients situation, it is possible to use the developed smartphone application either regularly or occasionally for making a measurement of the subject. The smartphone is placed on the chest of the patient who is adviced to lay down and perform a noninvasive recording, while no

ISSN2454-9940
www.ijsem.org
Vol 18, Issue.2 May 2024

external sensors are needed [9]. With the development of mobile Internet, various mobile applications have become increasingly popular. Many people are being benefited from the mobile healthcare services. Compared with the traditional healthcare services, patients medical behavior trajectories can be recorded by mobile healthcare services meticulously. They monitor the entire healthcare services process and help to improve the quality and standardization of healthcare services [10].

METHODOLOGY

The methodology for developing a cell app for cardiovascular sickness prediction the use of deep learning includes data collection, preprocessing, function engineering, version selection and improvement, schooling and validation, integration with the mobile app framework, testing, deployment, and ongoing maintenance and updates to make certain accuracy and usability. n cutting-edge age, smartphones are one of the maximum broadly utilized technologies worldwide and numerous telephone primarily based fitness apps are benefitting to humans. Development of a telephone based totally tool to predict coronary heart assault chance might advantage hundreds of humans. This motivates us to increase this project.

Any project is basically divided into many groups for easy understanding and coding. This paper consists of four which the application runs on. They are namely

1. User registration
2. Questionnaires
3. Checking the probability
4. Generating the report

USER REGISTRATION

Logging in, (or logging on or signing in or signing on), is the process by which an individual gains access to a computer system by identifying and authenticating themselves. The user credentials are typically some forms of “username” and a matching “password”, and these credentials themselves are sometimes referred to as a login.

QUESTIONNAIRES

Here the user feed the values in the application form, he/she fills up each and every details in the form. All these details get saved in the server and details and from that we can extract the features of the disease. The entered details are matched with the datasets which are saved in the database.

CHECK FOR THE DISEASE SYMPTOMS

After matching the details with the datasets, it checks for the disease symptoms. One feature may match with different disease. So, it’s necessary to check each and every matched detail in order to predict the correct disease.

GENERATE REPORT

A report is being generated based on the matched symptoms. It predicts the disease and send it to user mobile application, and

ISSN2454-9940

www.ijsem.org

Vol 18, Issue.2 May 2024

finally add some tips/suggestions to the user like nearby hospital details and it notifies patient by sending a message alert to patient mobile number

ARCHITECTURE DIAGRAM

Here, in architecture diagram it describes about the brief describes about the detailed information of process involved in cardiovascular diseases in DL. Firstly, Heart patient dataset is collected from the various hospitals and make a dataset and arrange the information and store the data, this stored data helps to identify the attributes that pertaining the heart diseases for the data domain. The data collected for the data domain helps for preparation and preprocessing the given data and this send to processing module to go through different data sets and Artificial neuro networks that helps for processing module, this helps to obtain results and compare and conclude the data.

DATASET DESCRIPTION

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940

www.ijsem.org

Vol 18, Issue.2 May 2024

The dataset used here for prediction of cardio vascular diseases prediction using deep learning is Logistic regression, K-NN classifier, SVM (support vector machine), Decision tree. Some parameters used in heart disease prediction include: Age, Fasting blood sugar, Max heart rate achieved and ST depression induced by exercise relative to rest.

Here, in architecture diagram it describes about the brief describes about the detailed information of process involved in cardiovascular diseases in DL. Firstly, Heart patient dataset is collected from the various hospitals and make a dataset and arrange the information and store the data, this stored data helps to identify the attributes that pertaining the heart diseases for the data domain. The data collected for the data domain helps for preparation and preprocessing the given data and this send to processing module to go through different data sets and Artificial neuro networks that helps for processing module, this helps to obtain results and compare and conclude the data.

RESULT ANALYSIS

We require to estimate the value function for determining the goodness of a particular action to be in a certain state. The notion of goodness of a specific action committed by the learning agent is determined on the basis of the number of expected future rewards and the precision in terms of expected number of returns. The value function for actions may be described as a specific way of acting as a consequence of the learning process based on the policies. For some state, considering the policy to be π, the value function can be denoted as υπ () and can hence be stated as the expectation value of return E θ, operating from some state and under policy π. Hence, we can obtain the formal definition of the value function for the MDPs as

$$v_\pi(s) = \mathbb{E}\left[\theta_t | S_t = s\right] \tag{1}$$

From the above (1),

the state-value function is obtained, where E [.] represents the expected value for some random variable under policy π and time frame . The return θ can be obtained for successive time frames of the learning system as,

$$\theta_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} \cdots + \gamma^i r_{t+j} \tag{2a}$$

$$\theta_t = r_{t+1} + \gamma\left(r_{t+2} + \gamma^1 r_{t+3} \cdots + \gamma^{i-1} r_{t+j}\right) \tag{2b}$$

$$\theta_t = r_{t+1} + \gamma\theta_{t+1} \tag{2c}$$

where r +j denotes the reward sequence such that r +j ∈ R, j = 1, 2, 3 m and γ i denotes the discount parameter for i = 0, 1, 2, . . . , n subject to the condition 0 ≤ γ ≤ 1. Now, by using the expression for return obtained we can modify Eq. (1) by recursively solving for policy π and state, we obtain

$$\upsilon_\pi\ (s) = \mathbb{E}_\pi\left[r_{t+1} + \gamma\theta_{t+1}|S_t = s\right] \tag{3a}$$

$$\upsilon_\pi\ (s) = \mathbb{E}_\pi\left[\sum_{k=0}^{\infty}\gamma^k r_{t+k+1}|S_t = s\right] \tag{3b}$$

The above expression in Eq.(3b) is referred to as the equation for state value function $\upsilon\pi$. Following the above convention for the state value function, the action value function for the above problem can be defined as the expected return or feedback from adopting action a for policy π can be stated as,

$$u_\pi\ (s, a) = \mathbb{E}_\pi\left[\theta_t|S_t = s, A_t = a\right] \tag{4}$$

Substituting the value in Eq.(2c) over the above equation we get,

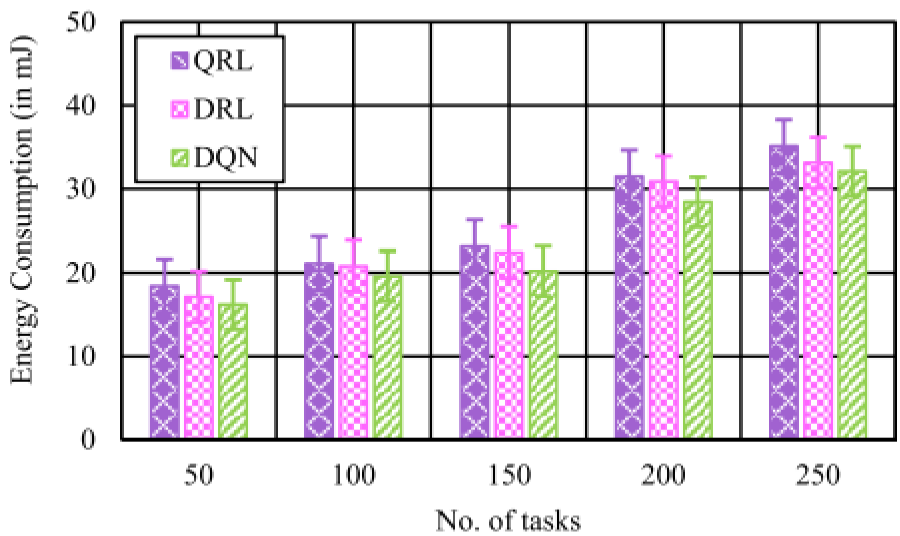
$$u_\pi\ (s, a) = \mathbb{E}_\pi\left[r_{t+1} + \gamma\theta_{t+1}|S_t = s, A_t = a\right] \tag{5a}$$

$$u_\pi\ (s, a) = \mathbb{E}_\pi\left[\sum_{k=0}^{\infty}\gamma^k r_{t+k+1}|S_t = s, A_t = a\right] \tag{5b}$$

We further estimate the Bellman's optimality equation to preserve self-consistency of state values in Eq.(3b). It makes intuitive sense that corresponding to an optimal policy, the value of a state must be equal to the average return pertaining to the best action undertaken by the learning agent from the state, and this can be defined as:

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT
ISSN2454-9940
www.ijsem.org
Vol 18, Issue.2 May 2024

GRAPH

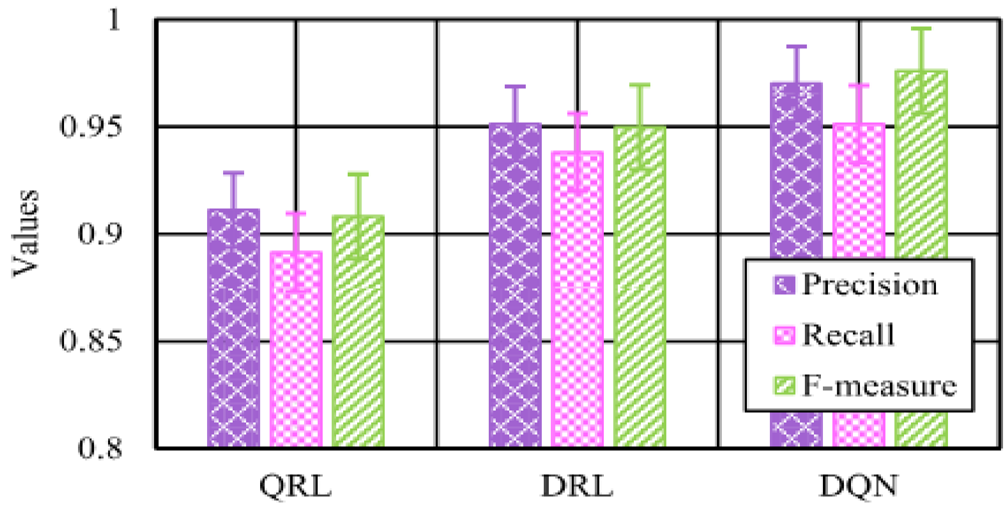


Comparison of energy consumption (in mj) for QRL, DRL, and DQN algorithms over varying tasks

No. of Tasks	QRL	DRL	DQN
50	18.4511	17.1347	16.2101
100	21.1261	20.8211	19.6014
150	23.1142	22.4142	20.1972
200	31.4712	30.8712	28.4312
250	35.1214	33.1011	**32.1002**

We analyse the energy consumption by the mist nodes for building the QRL, DRL, and DQN approach through our simulations. From above figure, the performance for the proposed DQN algorithm in convergence with the benchmark algorithms can be observed. From the figure it can be observed that the energy consumption entails an almost linear growth. The performance also depends upon the learning algorithm adopted. However, the proposed DQN algorithm outperforms all the other approaches in terms of minimizing the energy consumption in building the model over a mist computing environment. The highest energy consumed by the DQN algorithm for processing 250 tasks over the mist nodes was observed to be 32.1002 mj, whereas that of QRL and DRL algorithms were at 35.1214 mj and 33.1011 mj respectively. In Table the comparative study for energy consumed by QRL, DRL, and DQN algorithms for processing varying number of tasks over the mist nodes is provide

It's important to well known that even as this graph demonstrates the version's capability to examine from the training statistics, it doesn't always assure actual-international effectiveness. To ensure generalizability, comparing the model's performance on a separate validation dataset is critical. This validation system assesses the model's accuracy in classifying cardiovascular disease in unseen facts, presenting a extra reliable measure of its applicability in a scientific placing.



Comparison of performance like metrices like precision, recall and f – measure for QRL and DRL and proposed DQL algorithm.

MODELS			
	QRL	DRL	DQN
PRECISION	0.9112	0.9514	0.9701
RECALL	0.8914	0.9381	0.9512
F-MEASURE	0.9081	0.9498	0.9761

Values comparison for QRL, DRL and DQN algorithms form the given graph and different mathematical formulas and calculations.

$$P_r = \frac{T_p}{T_p + F_p} \ ; \ R = \frac{T_p}{T_p + F_n}$$

ISSN2454-9940

www.ijsem.org

Vol 18, Issue.2 May 2024

$$f - score = \frac{2*P*R}{P+R} ;\ A = \frac{Tp + Tn * 100}{(Tp + Tn\ )+(Fp + Fn)}$$

REFERENCES

[1] P. Tripathi et al., "Ensemble Computational Intelligent for Insomnia Sleep Stage Detection via the Sleep ECG Signal," in IEEE Access, vol. 10, pp. 108710-108721, 2022, doi: 10.1109/ACCESS.2022.3212120.

[2] M. Á. Goda and T. Telek, "A Phonography-Based Method Improved by Hidden Markov Model for Fetal Breathing Movement Detection," in IEEE Access, vol. 9, pp. 60154-60162, 2021, doi: 10.1109/ACCESS.2021.3072977.

[3] H. Charvátová, A. Procházka, O. Vyšata, C. P. Suárez-Araujo and J. H. Smith, "Evaluation of Accelerometric and Cycling Cadence Data for Motion Monitoring," in IEEE Access, vol. 9, pp. 129256-129263, 2021, doi: 10.1109/ACCESS.2021.3111323.

[4] Navaz AN, Serhani MA, El Kassabi HT, Al-Qirim N, Ismail H. Trends, Technologies, and Key Challenges in Smart and Connected Healthcare. IEEE Access. 2021 May 11;9:74044-74067. doi: 10.1109/ACCESS.2021.3079217.

[5] S. B. Shuvo, S. N. Ali, S. I. Swapnil, M. S. Al-Rakhami and A. Gumaei, "CardioXNet: A Novel Lightweight Deep Learning Framework for Cardiovascular Disease Classification Using Heart Sound Recordings," in IEEE Access, vol. 9, pp. 36955-36967, 2021, doi: 10.1109/ACCESS.2021.3063129.

[6] G. A. Tadesse et al., "Multi-Modal Diagnosis of Infectious Diseases in the Developing World," in IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 7, pp. 2131-2141, July 2020, doi: 10.1109/JBHI.2019.2959839.

[7] C. Navarro et al., "A Point-of-Care Measurement of NT-proBNP for Heart Failure Patients," in IEEE Access, vol. 8, pp. 138973-138983, 2020, doi: 10.1109/ACCESS.2020.3007988.

[8] A. K. Dwivedi, S. A. Imtiaz and E. Rodriguez-Villegas, "Algorithms for Automatic Analysis and Classification of Heart Sounds–A Systematic Review," in IEEE Access, vol. 7, pp. 8316-8345, 2019, doi: 10.1109/ACCESS.2018.2889437.

[9] O. Lahdenoja et al., "Atrial Fibrillation Detection via Accelerometer and Gyroscope of a Smartphone," in IEEE Journal of Biomedical and Health Informatics, vol. 22, no. 1, pp. 108-118, Jan. 2018, doi: 10.1109/JBHI.2017.2688473.

[10] Y. Gao, C. Sun, R. Li, Q. Li, L. Cui and B. Gong, "An Efficient Fraud Identification Method Combining Manifold Learning and Outliers Detection in Mobile Healthcare Services," in IEEE Access, vol. 6, pp. 60059-60068, 2018, doi: 10.1109/ACCESS.2018.2875516.