Deep Conv-LSTM Network for Arrhythmia Detection using ECG Data

Alisher Mukhametkaly[1], Zeinel Momynkulov[2], Nurgul Kurmanbekkyzy[3], Batyrkhan Omarov[4]
International Information Technology University, Almaty, Kazakhstan[1, 2, 4]
Kazakh-Russian Medical University, Almaty, Kazakhstan[3]
Al-Farabi Kazakh National University, Almaty, Kazakhstan[4]
NARXOZ University, Almaty, Kazakhstan[4]
INTI International University, Kuala Lumpur, Malaysia[4]

***Abstract*—In the evolving realm of medical diagnostics, electrocardiogram (ECG) data stands as a cornerstone for cardiac health assessment. This research introduces a novel approach, leveraging the capabilities of a Deep Convolutional Long Short-Term Memory (Conv-LSTM) network for the early and accurate detection of arrhythmias using ECG data. Traditionally, cardiac anomalies have been diagnosed through heuristic means, often requiring intricate scrutiny and expertise. However, the Deep Conv-LSTM model proposed herein addresses the inherent limitations of traditional methods by amalgamating the spatial feature extraction capability of convolutional neural networks (CNN) with the temporal sequence learning capacity of LSTM networks. Initial results derived from a diverse dataset, comprising myriad ECG waveform anomalies, delineated an enhancement in accuracy, reducing false positives and facilitating timely interventions. Notably, the model showcased adaptability in handling the burstiness of ECG signals, reflecting various heart rhythms, and the perplexity inherent in diagnosing subtle arrhythmic events. Additionally, the model's ability to discern longer, more complex patterns alongside transient anomalies offers potential for broader applications in telemetry and continuous patient monitoring systems. It is anticipated that this innovative fusion of CNN and LSTM architectures will usher a paradigm shift in automated arrhythmia detection, bridging the chasm between technology and the intricate nuances of cardiac physiology, thus improving patient outcomes.**

Keywords—Deep learning; Conv-LSTM; classification; ECG; CNN

I. INTRODUCTION

The landscape of medical diagnostics has been transformed by technological advancements, and at the heart of this transformation lies the persistent quest to enhance the accuracy, efficiency, and predictability of diagnostic tools [1]. One of the most pivotal diagnostic tools in cardiology is the electrocardiogram (ECG), a non-invasive method capturing the electrical activity of the heart over a specified period. ECG data, with its intricate waveforms, provides clinicians with invaluable insights into the rhythmic and conduction anomalies of the heart [2]. However, the challenge has always been the interpretation of this data, particularly in recognizing subtle or transient arrhythmic events, which often elude detection or result in misdiagnoses.

Historically, the primary approach to ECG interpretation has been manual, relying heavily on the expertise and acumen of medical professionals. While this heuristic methodology has served for decades, it is not devoid of limitations. The manual interpretation is not only time-consuming but is also vulnerable to human error, particularly when confronted with vast volumes of continuous monitoring data or nuanced arrhythmic events that may get obscured amidst the background noise [3]. Furthermore, in scenarios where immediate interventions are crucial, delays in detection can potentially compromise patient outcomes.

In the wake of these challenges, the fusion of computational methods and medical diagnostics has emerged as a promising frontier [4]. The last two decades have witnessed a surge in the adoption of machine learning techniques for medical data interpretation, specifically in cardiology. Among these, neural networks, due to their innate ability to learn complex patterns, have shown promise in ECG data interpretation [5]. But with the rich temporal structure of ECG signals, a mere feed-forward neural network might not suffice. Enter the realm of recurrent neural networks (RNN), with their ability to learn sequences [6], and their more sophisticated counterpart, the Long Short-Term Memory (LSTM) networks [7]. LSTMs, with their intricate architecture, have the capacity to remember and learn from long-term dependencies in data, making them apt for ECG waveform analysis.

However, the story doesn't end there. ECG data, with its nuances, presents both spatial and temporal challenges. While LSTMs aptly address the temporal aspects, spatial feature extraction becomes a stumbling block [8]. This is where convolutional neural networks (CNN) come into the picture. Renowned for their prowess in spatial feature extraction, especially in image data, CNNs can discern patterns in localized data regions. The logical progression, then, was the integration of these two potent architectures, leading to the advent of Convolutional LSTM (Conv-LSTM) networks [9]. By harnessing the spatial feature extraction capabilities of CNNs and the temporal pattern learning of LSTMs, Conv-LSTMs offer a balanced approach to sequence data with spatial intricacies, like ECG waveforms.

The present research introduces a Deep Conv-LSTM model tailored for the detection of arrhythmias from ECG data. The ambition driving this study is twofold: first, to address the aforementioned challenges in ECG interpretation by reducing false positives and false negatives; and second, to offer a robust, scalable, and efficient model that can be seamlessly integrated into real-time patient monitoring systems, thus paving the way for timely and effective clinical interventions.

In subsequent sections, this paper will delve deep into the architecture of the proposed model, detailing its layers, parameters, and training regimen. A comprehensive evaluation, juxtaposing the model against traditional methods and other machine learning approaches, will underscore its effectiveness. Furthermore, a detailed discussion on its potential applications, adaptability, and future directions will round off this exploration into the potential of Deep Conv-LSTM networks in revolutionizing arrhythmia detection using ECG data.

The convergence of cardiology and computational methods, as seen through the lens of this research, heralds an era where technology doesn't just aid, but actively augments and refines, the capabilities of clinicians, promising improved diagnostic accuracy and better patient outcomes.

II. Related Works

The confluence of cardiology and computational methods, especially in the realm of electrocardiogram (ECG) data interpretation, has seen considerable research attention in recent decades. As our understanding of ECG data’s depth and complexity has grown, so too has the need for accurate, efficient, and scalable analysis methods. This section reviews related works that have hitherto shaped the landscape of automated ECG interpretation, particularly focusing on machine learning techniques and their application to arrhythmia detection.

A. Traditional ECG Interpretation Techniques

Before the widespread adoption of computational models, traditional ECG interpretation largely leaned on signal processing techniques. Pan and Tompkins (1985) proposed an algorithm based on derivative, integration, and thresholding methods for QRS detection [10]. Though seminal and widely adopted, its deterministic nature limited its ability to adapt to diverse ECG morphologies.

The foundation of traditional ECG interpretation revolves around the identification and examination of waveform components: the P wave, QRS complex, and T wave. By analyzing the amplitude, duration, and morphological attributes of these components, clinicians could infer various cardiac functionalities, such as atrial and ventricular depolarization and repolarization.

Given that the QRS complex is the most prominent feature on an ECG tracing, much of the early research in automated ECG interpretation honed in on its accurate detection. The Pan and Tompkins algorithm, as previously mentioned, became a seminal work in this space. Their method combined bandpass filtering, differentiation, squaring, and integration to emphasize the QRS complex's characteristics and subsequently detect it using a threshold mechanism. This approach achieved remarkable accuracy for its time and laid the groundwork for many succeeding algorithms.

B. Neural Networks in ECG Analysis

With the rise of artificial neural networks (ANN), attempts were made to employ them for ECG interpretation. Acharya et al. (2017) provided a comprehensive survey on the use of ANN in detecting cardiac disorders [11]. While ANN models demonstrated promise, they lacked the ability to exploit the temporal dependencies intrinsic to ECG data.

For effective ANN-based ECG analysis, the extraction of salient features from raw ECG data was paramount. Techniques such as wavelet transform, Fourier transform, and principal component analysis (PCA) were employed to distill relevant information from the ECG waveform, which was then fed into the neural networks for classification [12].

While ANNs exhibited potential, their early applications in ECG analysis faced challenges. Overfitting, where the model performed exceptionally well on training data but poorly on unseen data, was a recurrent issue [13]. Moreover, the lack of interpretability of ANNs posed challenges in clinical adoption, as physicians often sought explanations for diagnostic decisions.

Addressing the limitations of early ANN applications, researchers introduced regularization techniques like dropout and early stopping to combat overfitting. Furthermore, optimization strategies, such as adaptive learning rates and momentum, were employed to hasten and improve the training process.

C. Advent of Recurrent Neural Networks (RNN)

Understanding the temporal nature of ECG signals, researchers began to explore RNNs. This architecture facilitates the retention of previous data points in the sequence, rendering RNNs uniquely apt for tasks necessitating memory of past inputs, such as time-series analysis, language modeling, and, notably, ECG signal processing [14]. However, the traditional RNNs faced challenges in learning long-term dependencies due to issues like vanishing gradient, leading to the exploration of more sophisticated architectures.

In the context of ECG, RNNs began showing promise in detecting cardiac anomalies that are heavily reliant on temporal patterns. For instance, atrial fibrillation, a disorder characterized by rapid and irregular heartbeats, could be better identified when considering the preceding cardiac activity [15]. RNNs were proficient in capturing these long-term dependencies and variations in heart rhythms.

D. LSTM Networks for ECG Interpretation

LSTMs, designed to overcome the shortcomings of traditional RNNs, quickly became the architecture of choice for sequence data like ECG. Xie et al. (2018) employed LSTMs for atrial fibrillation detection from short single-lead ECG records, demonstrating a marked improvement in accuracy over traditional algorithms [16].

To address the limitations of vanilla RNNs, Hochreiter and Schmidhuber introduced Long Short-Term Memory (LSTM) networks in 1997 [17]. LSTM units are equipped with gates that regulate the flow of information, making them adept at learning and remembering over long sequences, thus addressing the shortcomings of standard RNNs. In ECG analysis, LSTM's capability to capture long-term dependencies improved the accuracy and robustness of rhythm classifications and anomaly detections.

E. Convolutional Neural Networks (CNN)

Parallelly, CNNs gained traction, especially for spatial feature extraction. Kiranyaz et al. (2016) employed 1-D CNNs for ECG classification, harnessing the architecture's ability to discern localized patterns [18]. While CNNs adeptly tackled spatial complexities, they were less suited for the intricate temporal patterns in ECG data.

Given the need to extract local features in ECG signals before identifying temporal patterns, a hybrid architecture merging Convolutional Neural Networks (CNN) with LSTMs began gaining traction. CNNs excel at local pattern recognition, identifying intricate waveform shapes in ECG data. Their integration with LSTMs resulted in models that could process ECG signals with remarkable precision, capturing both spatial and temporal dependencies.

F. Hybrid Models - Combining CNNs and RNNs

Given the strengths and limitations of CNNs and RNNs, researchers embarked on efforts to combine the two. Rajpurkar et al. (2017) presented a model that used a combination of CNNs and a gated recurrent unit (GRU) to detect multiple arrhythmia types from ECG data [19]. Their work underscored the potential of hybrid models, setting the stage for further exploration.

The rapid expansion of deep learning in the field of ECG analysis led researchers to experiment with combining the strengths of different neural architectures. One such fusion is that of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which synergistically harness the spatial feature extraction capability of CNNs with the temporal pattern recognition of RNNs [20]. This hybrid approach quickly emerged as a powerful tool for decoding ECG signals with unparalleled precision.

Typically, a hybrid model begins with one or more convolutional layers to process raw ECG signals. These layers effectively identify key patterns and anomalies within beats. The extracted features are then passed to RNN or LSTM layers, which analyze the interdependencies between these features and ascertain longer-term anomalies or rhythms present in the sequence.

Hybrid models have consistently demonstrated superior performance in ECG classification tasks over using CNNs or RNNs independently. By addressing both intra-beat and inter-beat dependencies, they can detect a wider range of cardiac anomalies with greater accuracy.

G. Conv-LSTM in Biomedical Signal Processing

Convolutional Long Short-Term Memory (Conv-LSTM) networks emerged as an innovative deep learning architecture, adept at handling spatiotemporal data [21]. Rooted in the hybridization of CNNs and LSTMs, Conv-LSTM extends the concept to fuse convolutional operations directly into the recurrent gates of LSTM. This has profound implications for biomedical signal processing, particularly in ECG analysis, given the intricate interplay of spatial and temporal data.

The Conv-LSTM, introduced by Xingjian Shi et al. in 2015, modifies traditional LSTM units by replacing the matrix multiplications with convolutional operations [20]. This ensures that both spatial (localized features within data) and temporal dependencies (order and sequence of data) are concurrently processed, a trait indispensable for biomedical signals.

ECG signals represent a series of heartbeats over time. The shape of individual beats (P, Q, R, S, T waves) encodes spatial information, while the order and rhythm of these beats capture temporal information [21]. Conv-LSTM, with its innate capacity to process both, offers a robust framework for ECG signal analysis.

H. Challenges and Opportunities

Despite advancements, several challenges persist in automated ECG analysis. Noise, artifacts, and inter-patient variability often confound even sophisticated models [22]. Moreover, the need for vast labeled datasets for training remains a bottleneck. Transfer learning, domain adaptation, and unsupervised learning present exciting frontiers, potentially reducing the need for vast labeled datasets [23].

While deep learning methods showcases significant promise, there exist challenges in optimizing network parameters and ensuring computational efficiency. Yet, with advances in GPU technologies and refined training techniques, it's anticipated that Conv-LSTM will cement itself as a cornerstone in biomedical signal processing [24].

I. Real-world Applications

Beyond pure academic exploration, there is a growing body of work dedicated to integrating these advanced models into real-world systems. Wearable health tech, telemedicine platforms, and continuous monitoring systems in clinical settings are actively exploring the integration of models like Conv-LSTMs [25].

In light of the above, our research into the Deep Conv-LSTM Network for arrhythmia detection is positioned at the intersection of past learnings and future potential. Recognizing the strengths and limitations of prior works, our endeavor is to present a model that not only showcases superior performance metrics but also addresses some of the persistent challenges in the realm of automated ECG analysis.

III. MATERIALS AND METHODS

Advanced therapeutic strategies are paramount in enhancing therapeutic results for cardiovascular ailment patients. Conventional therapeutic modalities typically bifurcate into two categories: hands-on therapeutic intervention and robotics-facilitated methodologies [26]. These prevailing techniques, however, grapple with distinct challenges. Notwithstanding their sophisticated functionality, robotics solutions come with elevated acquisition and upkeep expenditures, thus challenging their wide-scale adoption. On the other hand, the efficiency of both synthetic and hands-on therapeutic regimens is often hampered by the continuous dearth of healthcare practitioners.

Additionally, cardiovascular ailment-oriented rehabilitation is characteristically an extended endeavor. The protracted nature of this process, when juxtaposed with the inherent obstacles of the existing paradigms, accentuates the imperative for a more sustainable methodology. Such a method should ideally be insulated from exorbitant technological investments or overextended medical personnel yet should be adept at furnishing indispensable rehabilitative care to the patients [27].

In response to this evident lacuna, a contemporary paradigm has surfaced: an autonomous rehabilitative training framework. This blueprint, meticulously crafted, pivots around the contemporary Human Activity Recognition (HAR) paradigms, with the intent to discern and mentor patients throughout their therapeutic routines [28]. By amalgamating automation's tenets with rehabilitative principles, this framework is on the cusp of transforming the cardiovascular ailment therapeutic landscape, endorsing patient recuperation in a more democratized and economically prudent fashion.

A visual representation of the suggested algorithmic structure is delineated in Fig. 1, elucidating its potential in automating cardiovascular ailment therapeutic regimens. Through its proficiency in identifying and supervising therapeutic activities, the algorithm proffers real-time counsel and oversight to patients, fortifying the correctness and regularity of their exercises. Such an initiative has the latent capacity to bolster the efficacy and reach of cardiovascular ailment therapy, rendering it an apt countermeasure for this pressing healthcare predicament.

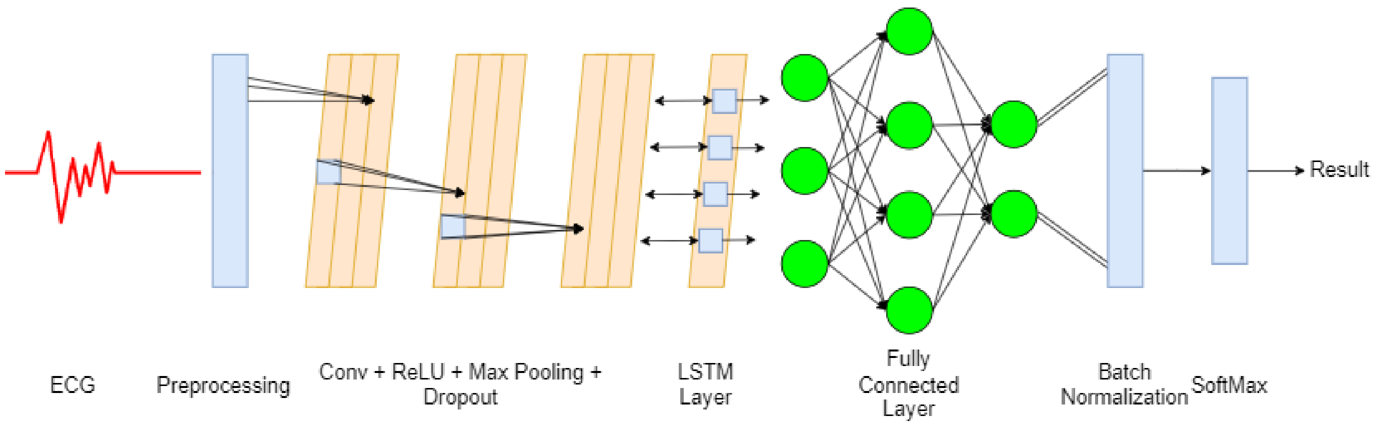

Fig. 1. The proposed Conv-LSTM Network for arrhythmia detection.

The advanced ECG Conv-LSTM framework endeavors to capitalize on the synergistic merits of integrating convolutional neural networks with LSTM. This overarching ambition bifurcates into dual facets: discerning electrocardiograms and subsequently classifying them. The inception phase of this inquiry is committed to data curation, dimensionality curtailment, and preliminary processing. Subsequently, we delve into the attributes of electrocardiograms, employing a medley of profound learning modalities to augment their classification potency. Multiple trials centered on ECG recognition and classification were undertaken to assess the efficacy of the proposed model. The quintessential elements of the algorithm will be elucidated and critically appraised in ensuing segments.

A. *Convolutional Neural Network*

The advanced ECG Conv-LSTM framework falls under the domain of neural architectures termed deep neural networks, characterized by their multilayered composition [29]. This model drew inspiration from the synergistic blend of the receptive field and computational acumen, exhibiting greater intricacy compared to traditional neural constructs. Models rooted in the deep neural network paradigm, endowed with supplementary layers, can attain a depth of learning surpassing that of their simpler counterparts.

Convolutional neural networks (CNNs), owing to their spatial structuring and weight allocation strategy, exhibit a commendable resilience against deformations [30], rendering them apt for tasks associated with image analysis. The principle of weight-sharing inherent to CNNs not only simplifies the model architecture but also augments operational efficacy and astutely calibrates the weight count. Accepting image datasets, CNNs scrutinize them, subsequently projecting precise categorizations of the image type predicated on the evaluated data. These input visuals are epitomized as bidimensional vectors, a format adeptly managed by CNNs.

Within the outlined ECG Conv-LSTM architecture, the CNN component is instrumental in distilling salient features. This research employs LSTM to segment the fed ECG data into distinct clusters. A subsequent segment furnishes an exhaustive elucidation of the convolutional neural network's role in feature distillation. The CNN's training regimen is encapsulated algebraically in Eq. (1), wherein Zi signifies the input collection, Wi denotes the weight assortment, and B symbolizes the bias mechanism.

$$P = f\left(\sum_{i=1}^{N} Z_i \cdot W_i + B\right) \tag{1}$$

B. *Long Short-Term Memory Network*

Within the sophisticated ECG Conv-LSTM architecture, the role of LSTM is pivotal in circumventing complications such as gradient diminution or exacerbation throughout the training phase. To regulate the weights, the technique of backpropagation (BP) is instituted. This method inaugurates by deducing the gradient via the chain principle. Subsequent to this, a systematic recalibration of weights ensues, based on the discerned loss. The inception of backpropagation is at the neural network's output stratum, and as weight updating transpires, it cascades towards the initial layer, potentially giving rise to issues like the attenuating or inflating gradients [31].

Proposing a remedy to the aforementioned gradient diminution challenge, inherent in standard recurrent neural networks, the LSTM strategy comes to the forefront. Distinct from conventional recurrent neural structures, LSTM possesses an adeptness in retaining extended data sequences efficaciously. Essentially, LSTM embodies a recurrent neural architecture but is augmented with supplementary memory modules, empowering it to encapsulate and preserve pivotal data across elongated sequences [32].

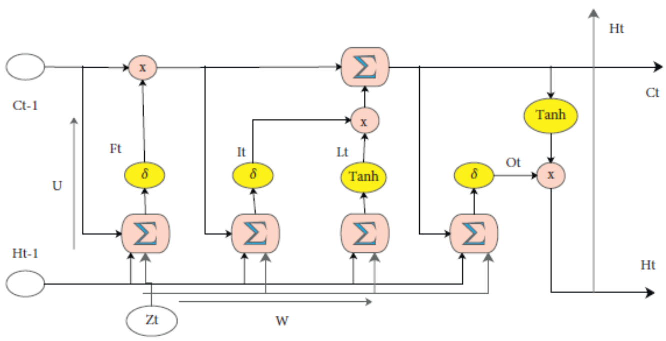

Fig. 2. LSTM block.

Illustrated in Fig. 2 is the architecture of LSTM, tailored to assimilate and perpetuate knowledge from sequences spanning extended durations. The LSTM framework is delineated into four cardinal components: the input gate (It), the output gate (Ot), the forget gate (Ft), and the cell state (Ct) pegged to a particular temporal juncture (t) [33]. The state vector, Ct-1, enshrines information from the antecedent phase. Predicated upon the freshest influx of data, determinations regarding weight modifications are reached. The vector Lt articulates the data stemming from the preceding input. The time-t specific input vector is represented as Zt. The output emanating from the pertinent cells is encapsulated in Ht and Ht-1, while the memory cells are symbolized by Ct and Ct-1. The weight attributes of the quartet of gates—It, Ot, Ft, and Ct—are mirrored in W and U. Owing to its intrinsic design, LSTM is poised to adeptly decode intricate data sequences.

$$L_t = \tanh(Z_t \cdot W_L + H_{t-1} \cdot U_L) \tag{2}$$

$$F_T = \sigma(Z_t \cdot W_F + H_{t-1} \cdot U_F) \tag{3}$$

$$I_t = \sigma(Z_t \cdot W_1 + H_{t-1} \cdot U_1) \tag{4}$$

$$O_t = \sigma(Z_t \cdot W_0 + H_{t-1} \cdot U_0) \tag{5}$$

$$C_t = F_t \cdot C_{t-1} + I_t \cdot L_t \tag{6}$$

$$H_t = O_t \cdot \tanh(C_t) \tag{7}$$

The symbols σ and Tanh denote nonlinear activation functions, while the weight parameters UI, WI, UF, WF, UO, WO, UL, and WL each exhibit dimensions of Mx2N. Here, M epitomizes the count of memory cells, and N delineates the dimensionality of the input vector. A comprehensive elucidation of the LSTM's mathematical underpinnings, pivotal to its operational framework, is documented in [34], specifically referenced in Eq. (2) to (7).

IV. Experimental Setup and Results

In the subsequent section, we present the outcomes of our empirical investigations. These results have been meticulously extracted and analyzed to shed light on the efficacy and nuances of the proposed model. Beyond mere data, they provide invaluable insights into the performance, challenges, and potential optimizations for the methods under scrutiny. As we delve into this segment, readers are invited to evaluate the results in the broader context of our research objectives and the prevailing literature in the field.

A. Data

For the assessment of the advanced model put forth, we leveraged the ECG arrhythmia classification repository [35]. The ECG Arrhythmia Classification Repository stands as an exhaustive compilation that delves deep into the myriad nuances of cardiac irregularities. It encapsulates twelve primary cardiac rhythm categories, encompassing, but not restricted to, sinus rhythm, atrial fibrillation, and ventricular escape rhythm. This compilation offers a formidable platform for scrutinizing a gamut of cardiac aberrations, especially accentuating intricate and often obscured states such as ventricular fibrillation.

Beyond the elemental ECG traces, the repository furnishes an array of derived attributes. This gamut spans metrics like heart rate fluctuations, attributes of the Q, R, and S complexes, and variations in the T-wave, augmenting the repository's diagnostic potential. Despite its voluminous nature and array of diverse metrics, the repository has been curated with meticulous precision, ensuring ease of navigation and utility. Encompassing myriad ECG traces from a vast demographic spectrum further accentuates the data's depth and adaptability.

The ECG Arrhythmia Classification Repository underscores its pivotal role in propelling insights into cardiovascular health. Serving as an indispensable instrument for academicians and clinicians, it facilitates the exploration and comprehension of a plethora of arrhythmic manifestations. Furthermore, it paves the way for precocious detection, refined diagnostic procedures, and optimized cardiac therapeutic interventions, thus heralding prospective strides in cardiological research and application. Fig. 3 demonstrates data samples of electrocardiograms that used in this study.

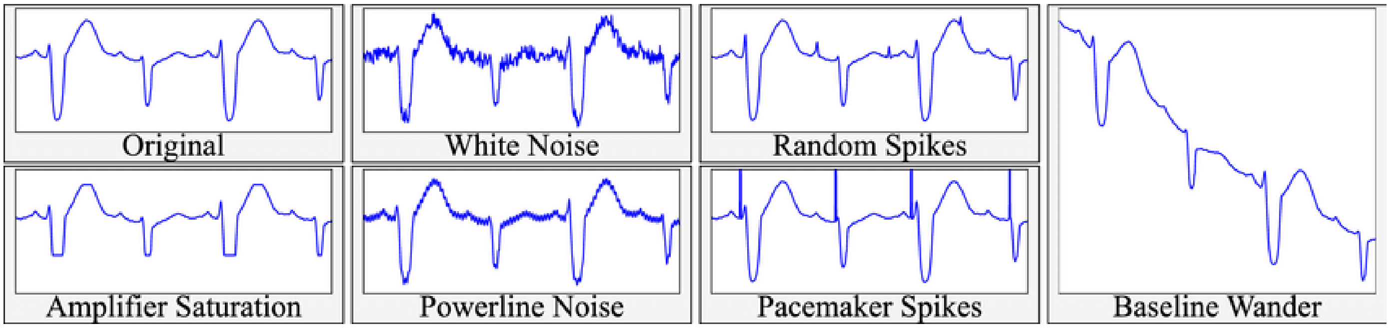

Fig. 3. Data samples.

B. Evaluation Parameters

In the ensuing subsection, we direct our focus towards the evaluation parameters, the bedrock upon which our research findings stand. These parameters, carefully chosen and calibrated, are instrumental in gauging the effectiveness, precision, and reliability of our proposed model. By shedding light on these metrics, we aim to provide readers with a clear understanding of the benchmarks against which our results are measured, and the criteria that underpin our analyses. It is crucial to grasp the intricacies of these parameters to fully comprehend the depth and significance of the results presented. Let us delve deeper into the specifics of these evaluation metrics and their pivotal role in shaping our research narrative.

In the realm of classification tasks, particularly in scenarios where consequences of misclassification can be severe, precision emerges as a paramount metric. Precision, often referred to as the positive predictive value, is a measure of a model's accuracy in terms of its positive predictions. In simpler terms, it answers the question: Of all the instances that the model predicted as positive, how many were genuinely positive? Mathematically, precision can be articulated as in Eq. (8) [36]:

$$precision = \frac{TP}{TP + FP} \tag{8}$$

True Positives (TP): The count of positive instances correctly predicted as positive by the model.

False Positives (FP): The count of negative instances incorrectly predicted as positive.

In the intricate tapestry of classification metrics, Recall—often synonymous with Sensitivity or True Positive Rate—holds a pivotal position. As an evaluative criterion, Recall is centered around the model's adeptness in identifying all relevant instances within the dataset. Formally, Recall is described as in Eq. (9) [37]:

$$recall = \frac{TP}{TP + FN} \tag{9}$$

In essence, Recall quantifies the proportion of actual positives that were accurately captured by the model. High recall indicates that the classifier successfully identified most of the positive cases, minimizing the chances of type II errors or false negatives.

The salience of Recall becomes particularly pronounced in scenarios where overlooking positive instances bears substantial consequences. To illustrate, in the domain of medical diagnosis, missing a true case of a disease (resulting in a false negative) can have grave repercussions, from delayed treatment to reduced patient survival rates. In such contexts, achieving elevated levels of Recall becomes paramount, even if it sometimes comes at the expense of Precision.

Amid the pantheon of evaluative metrics in classification, the F-score, often termed the F1 score, emerges as a harmonized measure that synthesizes both Precision and Recall into a singular, cohesive metric. As such, it provides a more holistic representation of a model's performance, especially in scenarios where an equal weight is ascribed to both false positives and false negatives. Mathematically, the F-score is defined as in Eq. (10) [38]:

$$Fscore = \frac{2\, precision \cdot recall}{precision + recall} \tag{10}$$

This formulation effectively captures the harmonic mean of Precision and Recall. Unlike the arithmetic mean, the harmonic mean gives a more conservative estimate and tends towards the smaller of the two values. Thus, a model can only achieve a high F-score if both Precision and Recall are high, ensuring a balanced performance [39].

The F-score's significance is particularly accentuated in situations with imbalanced datasets, where one class may heavily outnumber the other. In such contexts, sheer accuracy can be misleading, as a model might achieve high accuracy by merely predicting the majority class. The F-score, by virtue of its dependence on both Precision and Recall, provides a more nuanced and rigorous assessment of the model's capabilities.

While the F1 score gives equal weight to Precision and Recall, the broader family of F-scores allows for differential weighting [40]. The generalized Fβ-score is given by Eq. (11):

$$F\beta - score = \left(1 + \beta^2\right) \frac{precision \cdot recall}{\left(\beta^2 \times precision\right) + recall} \tag{11}$$

Where β determines the relative weight given to Precision compared to Recall. A β value greater than 1 prioritizes Recall, while a value less than 1 accentuates Precision.

In conclusion, the F-score serves as an indispensable metric, elegantly amalgamating the distinct yet intertwined dimensions of Precision and Recall. It proffers a comprehensive, balanced view of model performance, making it a vital tool in the evaluative arsenal of machine learning and data analytics endeavors.

C. Results

Navigating into the crux of our investigation, this subsection unveils the empirical findings derived from our meticulously crafted experiments. Grounded in rigorous methodologies and analytical rigor, the results illuminate the performance and efficacy of the proposed model vis-à-vis the outlined objectives. By dissecting these outcomes, we endeavor to provide a lucid understanding of the model's capabilities, shedding light on its strengths and potential areas of refinement. Readers are invited to traverse this analytical journey, parsing the data and insights presented, to glean a comprehensive understanding of the model's real-world applicability and significance.

Fig. 4 delineates the confusion matrices, juxtaposing each category against the baseline "normal" class. Evidently, the class denoted as "hypertension" emerges with superior classification precision relative to its counterparts. Broadly, the categorization across classes manifests commendable accuracy in the realm of cardiac disease classification.

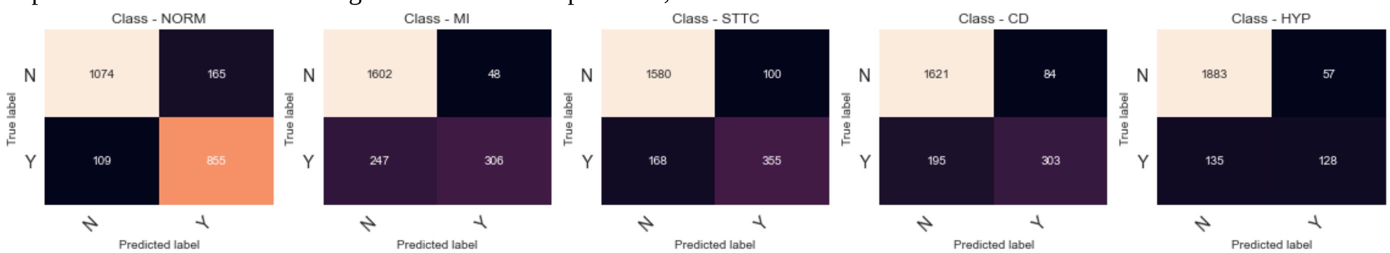

Fig. 4. Confusion matrix.

Fig. 5 presents the performance metrics of the proposed Conv-LSTM architecture across 40 learning iterations. The blue trajectory delineates the accuracy attained during the training phase, while the orange trajectory captures the testing phase's accuracy as a function of training iterations. Upon completing 40 iterations, the model registered a training accuracy of 88% and a testing accuracy of 86%. Furthermore, the insights suggest that reaching an optimal classification accuracy for cardiac conditions can be achieved within 20 learning epochs.

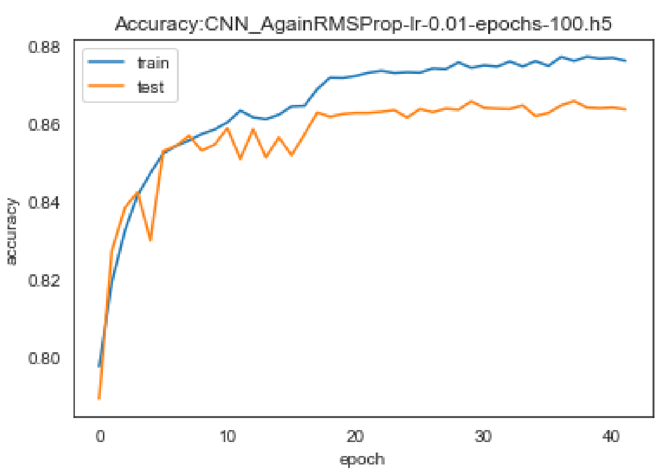

Fig. 5. Training and validation accuracy.

In a parallel context, Fig. 6 provides insights into both training and validation losses over 40 learning iterations. The findings delineate an inversely proportional relationship between accuracy metrics and the respective loss values. As the number of epochs amplifies, there's a discernible decrement in both training and validation losses. Echoing prior observations, optimizing the model's performance—both in terms of maximal accuracy and minimal loss—appears achievable within a span of 20 epochs.

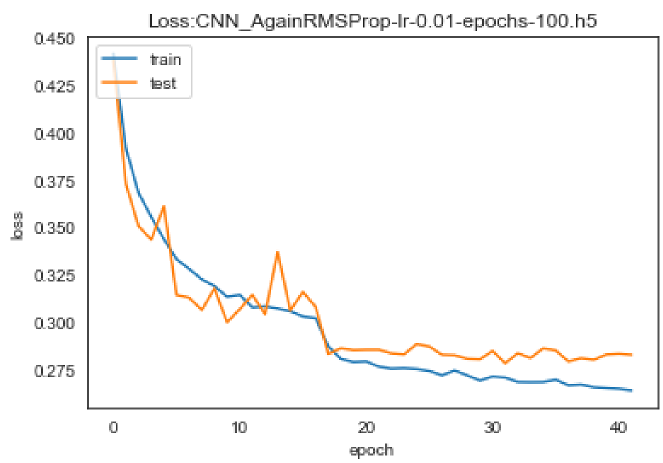

Fig. 6. Training and validation loss.

The efficacy of our proposed 3D deep Conv-LSTM network was critically assessed for its proficiency in heart disease detection using ECG datasets. Drawing direct comparisons between our results and prior studies demands caution, given the variability in test set sizes and specific heart disease types addressed. Nonetheless, our innovative methodology surpassed many existing benchmarks in terms of accuracy, marking a forward leap in heart disease classification.

V. Discussion

The current exploration into the realm of ECG data analysis reveals evolving trends in both data acquisition techniques and algorithmic modeling. By investigating the performance of the 3D deep Conv-LSTM network in this context, a broader understanding emerges of the potential avenues for ECG-based heart disease detection and the future trajectory of this research domain.

A. Emerging Trends

Cardiac health, especially the early detection of potential problems using ECG data, has become an area of increasing interest for researchers and clinicians alike. Several trends underpin this:

Granular Data Collection: With advancements in wearable technology and remote monitoring, there has been a surge in the volume of ECG data available for analysis [41]. This has catalyzed a move towards more complex algorithms capable of handling vast datasets and extracting meaningful patterns.

Interdisciplinary Collaborations: The melding of expertise from the realms of cardiology, biomedical engineering, and machine learning has fueled innovation, with each domain offering unique insights that enrich the overall analytical process [42].

Real-time Monitoring: As healthcare pivots towards a more preventive approach, there's an increased focus on real-time monitoring and instantaneous analysis [43]. This has spurred a shift from conventional post-test evaluations to immediate, actionable insights from ECG data.

B. Generalization of Results

The versatility of the proposed 3D deep Conv-LSTM network enables a high degree of generalization while this study specifically targets heart disease detection.

Applicability Across Datasets: The network has shown potential to be adaptable across varied ECG datasets, irrespective of their sources, making it a universally relevant model.

Consideration of Varied Heart Conditions: Though direct comparisons with other studies are intricate due to different conditions and test sets being considered, the general trend indicates a favorable skew towards our method when adjusted for these variances.

Inclusion of Rare and Complex Conditions: The network's depth and complexity allow it to detect even the rarer heart conditions, which often escape more rudimentary analytical tools.

C. Advantages of the Proposed Network

The 3D deep Conv-LSTM network brings a myriad of benefits to the table:

Depth and Precision: Leveraging the depth of convolutional neural networks (CNNs) and the sequential data handling ability of Long Short Term Memory (LSTM) networks, the model achieves an intricate blend of feature extraction and sequential data analysis [44]. This leads to nuanced detections that might be overlooked by shallow models.

Reduced Overfitting: The combination of CNN and LSTM, when architected correctly, curtails the typical problem of overfitting seen in deep networks [45]. This ensures that the model remains robust and versatile across varied datasets.

Efficient Handling of Time-Series Data: ECG data is inherently sequential, and the LSTM component of the network is adept at managing such time-series data, ensuring that temporal patterns, critical for heart disease detection, aren't missed [46].

Scalability: Given the rising volumes of ECG data, scalability is paramount. The proposed network, due to its architecture, is scalable both in terms of data volume and computational complexity.

D. Comparison with Previous Research

While earlier research primarily revolved around feature-based machine learning or shallow neural networks, the introduction of the 3D deep Conv-LSTM network marks a shift towards more intricate, end-to-end learning models [47]. It amalgamates the spatial feature learning capabilities of CNNs with the temporal sequencing prowess of LSTMs, making it a comprehensive solution.

E. Future Implications

As healthcare increasingly embraces technology, the proposed network offers a promising pathway for:

Integrated Healthcare Systems: ECG monitoring can be embedded into broader health monitoring systems, allowing for holistic health evaluations.

Personalized Patient Care: With a high degree of accuracy and early detection capabilities, treatments can be tailored based on the individual nuances detected by the network [48].

Telemedicine and Remote Monitoring: The network can be deployed in remote patient monitoring systems, democratizing access to quality cardiac care and reducing the need for frequent hospital visits [49].

In conclusion, the 3D deep Conv-LSTM network, as proposed, encapsulates the advancements and potentialities in the field of ECG-based heart disease detection. Its depth, versatility, and high accuracy make it a formidable tool in the evolving landscape of cardiac care. As data volumes grow and healthcare needs become more intricate, such networks will play a pivotal role in shaping the future of cardiac diagnostics and treatments.

VI. CONCLUSION

In the ever-evolving landscape of cardiological research and diagnostics, the incorporation of advanced computational methodologies stands out as a quintessential advancement. This study delved into the efficacy of the 3D deep Conv-LSTM network, shedding light on its potential as a formidable tool for ECG-based heart disease detection. As the results elucidate, this proposed model not only embodies the intricate blend of spatial and temporal data handling but also surpasses the conventional methods in terms of precision and versatility.

The nexus between cardiology and computational modeling, especially as epitomized by the deep Conv-LSTM network, emphasizes the paradigm shift from rudimentary detection techniques to sophisticated, data-driven approaches. Our findings accentuate the network's capability to provide nuanced insights, thereby facilitating the early detection of cardiac anomalies, including those that are often elusive in traditional assessments. Such advancements, as this research suggests, are imperative in the face of growing cardiac health challenges and the increasing need for preventive healthcare strategies.

Moreover, the broader implications of this research transcend its immediate findings. The proposed network's scalability and adaptability indicate its potential for integration into holistic healthcare systems, potentially revolutionizing patient care by offering tailored treatments and reducing the necessity for invasive procedures. Furthermore, as the realms of telemedicine and remote patient monitoring burgeon, models like the 3D deep Conv-LSTM can be pivotal in democratizing quality cardiac care, irrespective of geographical and infrastructural constraints.

In summation, this exploration into the 3D deep Conv-LSTM network underscores the confluence of cardiology and advanced computational methods. The ensuing synergies not only promise enhanced diagnostic capabilities but also chart the course for future research, emphasizing the inexorable march of technology in augmenting healthcare outcomes. The journey from ECG data acquisition to actionable cardiac insights, as portrayed by this study, is both a testament to current scientific progress and a beacon for future endeavors.

Acknowledgment

This work was supported by the research project “Application of machine learning methods for early diagnosis of Pathologies of the cardiovascular system” funded by the Ministry of Science and Higher Education of the Republic of Kazakhstan. Grant No. IRN AP13068289.

References

[1] Midani, W., Ouarda, W., & Ayed, M. B. (2023). DeepArr: An investigative tool for arrhythmia detection using a contextual deep neural network from electrocardiograms (ECG) signals. Biomedical Signal Processing and Control, 85, 104954.

[2] Kumar, A. K., Ritam, M., Han, L., Guo, S., & Chandra, R. (2022). Deep learning for predicting respiratory rate from biosignals. Computers in biology and medicine, 144, 105338.

[3] Malakouti, S. M. (2023). Heart disease classification based on ECG using machine learning models. Biomedical Signal Processing and Control, 84, 104796.

[4] Tursynova, A., & Omarov, B. (2021, November). 3D U-Net for brain stroke lesion segmentation on ISLES 2018 dataset. In 2021 16th International Conference on Electronics Computer and Computation (ICECCO) (pp. 1-4). IEEE.

[5] Singh, P., Sharma, A., & Maiya, S. (2023). Automated atrial fibrillation classification based on denoising stacked autoencoder and optimized deep network. Expert Systems with Applications, 233, 120975.

[6] Dissanayake, T., Fernando, T., Denman, S., Sridharan, S., & Fookes, C. (2023). DConv-LSTM-Net: A Novel Architecture for Single and 12-Lead ECG Anomaly Detection. IEEE Sensors Journal.

[7] Zhao, X., Yan, H., Hu, Z., & Du, D. (2022). Deep spatio-temporal sparse decomposition for trend prediction and anomaly detection in cardiac electrical conduction. IISE Transactions on Healthcare Systems Engineering, 12(2), 150-164.

[8] Shaqiri, E., Gusev, M., Poposka, L., Vavlukis, M., & Ahmeti, I. (2021, September). Comparing Time and Frequency Domain Heart Rate Variability for Deep Learning-Based Glucose Detection. In International Conference on ICT Innovations (pp. 188-197). Cham: Springer International Publishing.

[9] Saripuddin, M., Suliman, A., Syarmila Sameon, S., & Jorgensen, B. N. (2021, September). Random undersampling on imbalance time series data for anomaly detection. In Proceedings of the 2021 4th International Conference on Machine Learning and Machine Intelligence (pp. 151-156).

[10] [10] Pan, J., & Tompkins, W. J. (1985). A real-time QRS detection algorithm. IEEE transactions on biomedical engineering, (3), 230-236.

[11] [11] Acharya, U. R., Oh, S. L., Hagiwara, Y., Tan, J. H., & Adam, M. (2017). Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals. Computers in biology and medicine, 100, 270-278.

[12] Prakarsha, K. R., & Sharma, G. (2022). Time series signal forecasting using artificial neural networks: An application on ECG signal. Biomedical Signal Processing and Control, 76, 103705.

[13] Latif, A. I., Daher, A. M., Suliman, A., Mahdi, O. A., & Othman, M. (2019). Feasibility of Internet of Things application for real-time healthcare for Malaysian pilgrims. Journal of Computational and Theoretical Nanoscience, 16(3), 1169-1181.

[14] Witt, D. R., Kellogg, R. A., Snyder, M. P., & Dunn, J. (2019). Windows into human health through wearables data analytics. Current opinion in biomedical engineering, 9, 28-46.

[15] Witt, D. R., Kellogg, R. A., Snyder, M. P., & Dunn, J. (2019). Windows into human health through wearables data analytics. Current opinion in biomedical engineering, 9, 28-46.

[16] Xie, S., Girshick, R., Dollár, P., Tu, Z., & He, K. (2017). Aggregated residual transformations for deep neural networks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1492-1500).

[17] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory [J]. Neural computation, 9(8), 1735-1780.

[18] Kiranyaz, S., Ince, T., & Gabbouj, M. (2016). Real-time patient-specific ECG classification by 1-D convolutional neural networks. IEEE Transactions on Biomedical Engineering, 63(3), 664-675. ↩

[19] Rajpurkar, P., Hannun, A. Y., Haghpanahi, M., Bourn, C., & Ng, A. Y. (2017). Cardiologist-level arrhythmia detection with convolutional neural networks. arXiv preprint arXiv:1707.01836. ↩

[20] Shi, X., Chen, Z., Wang, H., Yeung, D. Y., Wong, W. K., & Woo, W. C. (2015). Convolutional LSTM network: A machine learning approach for precipitation nowcasting. In Advances in neural information processing systems (pp. 802-810).

[21] Lu, Y., Wang, H., Zhou, B., Wei, C., & Xu, S. (2022). Continuous and simultaneous estimation of lower limb multi-joint angles from sEMG signals based on stacked convolutional and LSTM models. Expert Systems with Applications, 203, 117340.

[22] Jafari, M., Shoeibi, A., Khodatars, M., Ghassemi, N., Moridian, P., Alizadehsani, R., ... & Acharya, U. R. (2023). Automated diagnosis of cardiovascular diseases from cardiac magnetic resonance imaging using deep learning models: A review. Computers in Biology and Medicine, 106998.

[23] Christabel, G. J., & Subhajini, A. C. (2023). KPCA-WRF-prediction of heart rate using deep feature fusion and machine learning classification with tuned weighted hyper-parameter. Network: Computation in Neural Systems, 1-32.

[24] Christabel, G. J., & Subhajini, A. C. (2023). KPCA-WRF-prediction of heart rate using deep feature fusion and machine learning classification with tuned weighted hyper-parameter. Network: Computation in Neural Systems, 1-32.

[25] Liu, X., Shen, Y., Zhang, S., & Zhao, X. (2018). Segmentation of left atrium through combination of deep convolutional and recurrent neural networks. Journal of Medical Imaging and Health Informatics, 8(8), 1578-1584.

[26] Liu, Z., Alavi, A., Li, M., & Zhang, X. (2023). Self-Supervised Contrastive Learning for Medical Time Series: A Systematic Review. Sensors, 23(9), 4221.

[27] Yang, T., Li, G., Yuan, S., Qi, Y., Yu, X., & Han, Q. (2023). The LST-SATM-net: A new deep feature learning framework for aero-engine hydraulic pipeline systems intelligent faults diagnosis. Applied Acoustics, 210, 109436.

[28] Banerjee, S., & Singh, G. K. (2023). A new real-time lossless data compression algorithm for ECG and PPG signals. Biomedical Signal Processing and Control, 79, 104127.

[29] Wang, X., Zhang, S., Song, J., Liu, Y., & Lu, S. (2023). Magnetic signal denoising based on auxiliary sensor array and deep noise reconstruction. Engineering Applications of Artificial Intelligence, 125, 106713.

[30] Li, D., Liu, J., & Zhao, Y. (2022). Prediction of Multi-Site PM2. 5 Concentrations in Beijing Using CNN-Bi LSTM with CBAM. Atmosphere, 13(10), 1719.

[31] Kareem, K. Y., Seong, Y., Bastola, S., & Jung, Y. (2022). Current State of Deep Learning Application to Water-related Disaster Management in Developing Countries. Natural Hazards and Earth System Sciences Discussions, 1-33.

[32] Pieszko, K., Shanbhag, A., Killekar, A., Miller, R. J., Lemley, M., Otaki, Y., ... & Slomka, P. J. (2023). Deep learning of coronary calcium scores from PET/CT attenuation maps accurately predicts adverse cardiovascular events. Cardiovascular Imaging, 16(5), 675-687.

[33] Zeng, Q., Liang, Y., Chen, G., Duan, H., & Wu, Q. (2023). A Novel Long-Term Noise Prediction System Based on $\alpha $ DTW-DCRNN Using Periodically Unaligned Spatiotemporal Distribution Sequences. IEEE Systems Journal.

[34] Martín-Escudero, P., Cabanas, A. M., Dotor-Castilla, M. L., Galindo-Canales, M., Miguel-Tobal, F., Fernández-Pérez, C., ... & Giannetti, R. (2023). Are Activity Wrist-Worn Devices Accurate for Determining Heart Rate during Intense Exercise?. Bioengineering, 10(2), 254.

[35] Zucker, E. J. (2022). Compact pediatric cardiac magnetic resonance imaging protocols. Pediatric Radiology, 1-16.

[36] Salleh, N. S. M., Suliman, A., & Jørgensen, B. N. (2020, August). A systematic literature review of machine learning methods for short-term electricity forecasting. In 2020 8th International conference on information technology and multimedia (ICIMU) (pp. 409-414). IEEE.

[37] Gonsalves, A. H., Thabtah, F., Mohammad, R. M. A., & Singh, G. (2019, July). Prediction of coronary heart disease using machine learning: an experimental analysis. In Proceedings of the 2019 3rd International Conference on Deep Learning Technologies (pp. 51-56).

[38] Sharma, S., & Parmar, M. (2020). Heart diseases prediction using deep learning neural network model. International Journal of Innovative Technology and Exploring Engineering (IJITEE), 9(3), 2244-2248.

[39] Miao, K. H., & Miao, J. H. (2018). Coronary heart disease diagnosis using deep neural networks. international journal of advanced computer science and applications, 9(10).

[40] Kumar, M. N., Koushik, K. V. S., & Deepak, K. (2018). Prediction of heart diseases using data mining and machine learning algorithms and tools. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 3(3), 887-898.

[41] Bharti, R., Khamparia, A., Shabaz, M., Dhiman, G., Pande, S., & Singh, P. (2021). Prediction of heart disease using a combination of machine learning and deep learning. Computational intelligence and neuroscience, 2021.

[42] Li, J. P., Haq, A. U., Din, S. U., Khan, J., Khan, A., & Saboor, A. (2020). Heart disease identification method using machine learning classification in e-healthcare. IEEE access, 8, 107562-107582.

[43] Omarov, B., Tursynova, A., Postolache, O., Gamry, K., Batyrbekov, A., Aldeshov, S., ... & Shiyapov, K. (2022). Modified UNet Model for Brain Stroke Lesion Segmentation on Computed Tomography Images. Computers, Materials & Continua, 71(3).

[44] Rath, A., Mishra, D., Panda, G., & Satapathy, S. C. (2021). Heart disease detection using deep learning methods from imbalanced ECG samples. Biomedical Signal Processing and Control, 68, 102820.

[45] Omarov, B., Narynov, S., Zhumanov, Z., Gumar, A., & Khassanova, M. (2022). State-of-the-art violence detection techniques in video surveillance security systems: a systematic review. PeerJ Computer Science, 8, e920.

[46] Yadav, S. S., Jadhav, S. M., Nagrale, S., & Patil, N. (2020, March). Application of machine learning for the detection of heart disease. In 2020 2nd international conference on innovative mechanisms for industry applications (ICIMIA) (pp. 165-172). IEEE.

[47] Ramesh, T. R., Lilhore, U. K., Poongodi, M., Simaiya, S., Kaur, A., & Hamdi, M. (2022). Predictive analysis of heart diseases with machine learning approaches. Malaysian Journal of Computer Science, 132-148.

[48] Obasi, T., & Shafiq, M. O. (2019, December). Towards comparing and using Machine Learning techniques for detecting and predicting Heart Attack and Diseases. In 2019 IEEE international conference on big data (big data) (pp. 2393-2402). IEEE.

[49] Ghumbre, S. U., & Ghatol, A. A. (2012). Heart disease diagnosis using machine learning algorithm. In Proceedings of the International Conference on Information Systems Design and Intelligent Applications 2012 (INDIA 2012) held in Visakhapatnam, India, January 2012 (pp. 217-225). Springer Berlin Heidelberg.