CLASSIFICATION OF ARRHYTHMIA BY USING DEEP LEARNING WITH 2-D ECG SPECTRAL IMAGE REPRESENTATION

LITERATURE SURVEY

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| S.NO | PAPER | AUTHOR | YEAR | SHORT | RESULT | FUTURE |
|------|----------------|-------------|------|--------------------------|------------------|---------------------|
| | | | | DESCRIPTION | | WORK AND |
| | | | | | | ANALYSIS |
| | | | | | | |
| 1. | Classification | Amin Ullah, | 2020 | The classification of | The proposed | Among all of the |
| 1. | of Arrhythmia | Syed Anwar, | 2020 | ECG data into eight | method | compared CNN |
| | by Using Deep | Muhammad | | classes using a two- | outperformed | algorithms, the |
| | Learning with | Bilal, Raja | | dimensional (2-D) | recently | suggested model |
| | 2-D ECG | Majid | | convolutional neural | reported | has acquired the |
| | Spectral | Mehmood | | network (CNN) model | findings in | highest |
| | Image | Wichinood | | is proposed. These | classifying | sensitivity. It is |
| | Representation | | | classes are normal beat, | similar types of | important to |
| | Representation | | | premature ventricular | arrhythmias, | remember that |
| | | | | contraction beat, paced | with an | finding these |
| | | | | beat, right bundle | average | cardiac |
| | | | | branch block beat, left | classification | arrhythmias |
| | | | | bundle branch block | accuracy of | requires a lot of |
| | | | | beat, atrial premature | 99.11% that is | work, requiring a |
| | | | | contraction beat, | at the cutting | clinical expert to |
| | | | | ventricular flutter wave | edge. The | meticulously |
| | | | | beat, and ventricular | success of the | review recordings |
| | | | | escape beat. Short-time | suggested | for up to hours at |
| | | | | Fourier transform is | strategy is | a time. By |
| | | | | used to convert the one- | demonstrated | identifying these |
| | | | | dimensional ECG time | by the | patterns and |
| | | | | series signals into two- | performance | prompting the |
| | | | | dimensional | being | observer to pay |
| | | | | spectrograms. The 2-D | significant in | closer attention to |
| | | | | CNN model is made to | additional | areas of greater |
| | | | | extract robust features | indices, such | significance, the |

| | | | | from the input spectrograms, and it has four convolutional layers and four pooling layers. | as sensitivity and specificity. | artificially intelligent system could improve the performance of clinical specialists. The clinical diagnosis and treatment of some of the major CVDs would ultimately benefit from this. |
|----|---|--|------|--|---|---|
| 2. | Cardiac arrhythmia detection using deep learning | Ali Isina, Selen Ozdalili | 2017 | In everyday clinical practise, an ECG is a crucial diagnostic tool for evaluating heart arrhythmias. By grouping patient ECGs into appropriate cardiac states, a deep learning framework that has previously been trained on a general picture data set is applied to carry out automatic ECG arrhythmia diagnosis. The final classification is carried out using a basic back propagation neural network using the features recovered by a transferred deep convolutional neural network, which is employed as a feature extractor. | We saw that the ECG data from the MIT-BIH database was pre-processed, that QRS complexes were found, and that characteristics from R-T intervals were retrieved. Networks based on transferable deep learning feature extraction obtained over 100% recognition rates and accuracies above 96% in the training phase, according to an evaluation of all the studied networks. | Deep learning applications will deliver cutting-edge results not just in medical signals and imaging diagnostics, but also in other popular subfields of biomedical imaging and signals. |
| 3. | Arrhythmia Classification Techniques Using Deep Neural Network | Ali Haider Khan,Muzam mi I Hussain ,and Muhammad Kamran Malik | 2021 | The automatic classification of arrhythmias based on ECG beats has been established for ages. The automatic | The use of imbalanced data for classification is the most significant | Automated arrhythmia identification necessitated feature extraction from ECG |

| F | _ | | | | | |
|----|----------------|---------------|----------|---------------------------|------------------|----------------------|
| | | | | arrhythmia | issue that | images, which |
| | | | | classification | affects the | called for subject- |
| | | | | algorithms built on | effectiveness | matter expertise. |
| | | | | deep learning are highly | of the | To prevent |
| | | | | accurate. The use of | established | overfitting, a |
| | | | | imbalanced data for | arrhythmia | balanced dataset |
| | | | | classification is the | detection | must be utilised |
| | | | | most significant factor | systems, along | with the |
| | | | | affecting the | with (i) | classification |
| | | | | effectiveness of the | manual feature | techniques. |
| | | | | created arrhythmia | selection, (ii) | |
| | | | | detection systems, | features | |
| | | | | along with (i) manual | extraction | |
| | | | | feature selection, (ii) | methods, and | |
| | | | | feature extraction | (iii) | |
| | | | | methods, and (iii) | classification | |
| | | | | classification algorithm. | algorithms. | |
| 4. | A deep | U. Rajendra | 2017 | The distinction between | The number of | The scientists |
| | convolutional | Acharya, Shu | | normal and irregular | instances of | hope to expand |
| | neural network | Lih Oh, Yuki | | heartbeats and their | each of the five | on their suggested |
| | model to | Hagiwara, Jen | | proper classification | kinds of | model in |
| | classify | Hong Tan, | | into various diseases | heartbeats in | subsequent |
| | heartbeats | Muhammad | | based on ECG | this set was | research by |
| | 110011000000 | Adam | | morphology form the | artificially | teaching a CNN |
| | | 1100111 | | foundation of | increased, and | to distinguish |
| | | | | arrhythmia diagnosis. | high-frequency | temporal patterns |
| | | | | Five categories of | noise was | of ECG heartbeat |
| | | | | heartbeats can be | removed by | data. The five |
| | | | | distinguished: non- | filtering. With | classes of ECG |
| | | | | ectopic, | the use of the | heartbeats (N, S, |
| | | | | supraventricular | enhanced data, | V, F, and Q) that |
| | | | | ectopic, ventricular | the CNN was | were taken into |
| | | | | ectopic, fusion, and | trained, and it | consideration in |
| | | | | unidentified beats. | was able to | this work can be |
| | | | | Distinguishing these | diagnose | categorised into |
| | | | | heartbeats on an ECG is | heartbeats in | three primary |
| | | | | difficult and time- | both the | groups: green, |
| | | | | consuming since these | original and | yellow, and red, |
| | | | | signals are frequently | noise-free | which stand for |
| | | | | distorted by noise. To | ECGs with an | normal, |
| | | | | automatically | accuracy of | abnormal, and |
| | | | | distinguish between | 94.03% and | possibly fatal |
| | | | | five different types of | 93.47%, | situations of heart |
| | | | | heartbeats in ECG | respectively. | electrical activity, |
| | | | | readings, we created a | When CNN | respectively. In |
| | | | | 9-layer deep | received | further studies, |
| | | | | convolutional neural | training from | the authors intend |
| | | | | network (CNN). Our | highly | to discuss the |
| | | | | ` , | Ingilly | |
| | | | | study used original and | | performance of |
| L | 1 | | <u> </u> | noise-attenuated sets of | | the CNN model |

| | T | T | T | I = ~ ~ | | |
|----|----------------|--------------|------|--------------------------|------------------|---|
| | | | | ECG signals that were | In noisy and | utilising de- |
| | | | | taken from a public | noise-free | skewed data as |
| | | | | database. | ECGs, | well as data that |
| | | | | | respectively, | has varied levels |
| | | | | | the accuracy of | of noise added. |
| | | | | | the CNN | |
| | | | | | dropped to | |
| | | | | | 89.07% and | |
| | | | | | 89.3% due to | |
| | | | | | | |
| | | | | | imbalanced | |
| | | | | | data (original | |
| | | | | | dataset). The | |
| | | | | | suggested | |
| | | | | | CNN model, | |
| | | | | | when correctly | |
| | | | | | trained, can be | |
| | | | | | used as a | |
| | | | | | screening tool | |
| | | | | | for ECGs to | |
| | | | | | swiftly identify | |
| | | | | | various types | |
| | | | | | and | |
| | | | | | frequencies of | |
| | | | | | arrhythmic | |
| | | | | | | |
| 5. | Classification | XX74 | 2021 | A: 41:6 | heartbeats. | C = 1 - 1 - 1 - 1 - 1 - 1 - 1 - 1 - 1 - 1 |
| 5. | | Wusat | 2021 | Aims to classify | With a 99.12 | Conducting this |
| | of Arrhythmia | Ullah,Imran | | arrhythmia using deep | percent | investigation |
| | in Heartbeat | Siddique, | | learning methods on a | accuracy rate | across |
| | Detection | Rana | | publically available | for the CNN | interconnected |
| | Using Deep | Muhammad | | dataset. The system | model, a 99.3 | areas like cloud |
| | Learning. | Zulqarnain, | | combines RR intervals, | percent | and mobile |
| | | Mohammad | | signal morphology, and | accuracy rate | systems is a good |
| | | Mahtab Alam, | | higher-level statistical | for the CNN + | idea. The |
| | | Irfan Ahmad, | | data, three independent | LSTM model, | development of |
| | | and Usman | | forms of information. | and a 99.29 | integrated low- |
| | | Ahmad Raza. | | The analysis of | percent | power |
| | | | | computerised ECGs | accuracy rate | consumption |
| | | | | using fuzzy-based | for the CNN + | wearable |
| | | | | technology is | LSTM + | technology is also |
| | | | | successful, although | Attention | crucial. |
| | | | | further study is | Model, it has | Cruciai. |
| | | | | _ | | |
| | | | | required. | the capacity to | |
| | | | | | make | |
| | | | | | extremely | |
| | | | | | precise | |
| | | | | | predictions. | |