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A Framework for Medical Data Analysis using Deep Learning Based on Conventional Neural Network (CNN) and Variable Auto-Encoder

Shaik Shabbeer, E. Srinivasa Reddy

Abstract*: Medical data classification is an important and complex task. Due to the nature of data, the data is in different forms like text, numeric, images and sometimes combination of all. The goal of this paper is to provide a high-level introduction into practical machine learning for purposes of medical data classification. In this paper we use CNN-Auto encoder to extract data from the medical repository and made the classification of heterogeneous medical data. Here Auto encoder uses to get the prime features and CNN is there to extract detailed features. Combination of these two mechanisms are more suitable for medical data classification. Hybrid AE-CNN (auto encoder based Convolutional neural network). Here the performance of proposed mechanism with respect to baseline methods will be assessed. The performance results showed that the proposed mechanism performed well.

***Keywords* : Conventional neural network, auto-encoder, medical data, MIMIC3.**

I. INTRODUCTION

Data [1] has changed the manner in which we oversee, investigate and influence information in any industry. A standout amongst the most encouraging territories where it tends to be connected to roll out an improvement is human services. Human services examination can possibly diminish expenses of treatment, foresee flare-ups of pestilences, maintain a strategic distance from preventable maladies and improve the personal satisfaction when all is said and done. Normal human future is expanding along total populace, which stances new troubles to the present treatment conveyance strategies. Wellbeing specialists, much the same as business individuals, are fit for gathering gigantic measures of information and search for best systems to use these numbers.

Health care associations over the US have made the change from paper-based report to the executive's frameworks in putting away records electronically. An electronic wellbeing record (EHR) [1] [2] is a mechanized gathering of patient data in an advanced arrangement. The significance of electronic wellbeing records is that they encourage sharing of patient information, for example, therapeutic records, diagrams, prescriptions and test results over numerous human service conditions.

Health care data analysis gives numerous advantages as follows: Occurrences of the different favorable circumstances of electronic medicinal records in centers and other social protection workplaces which include: Improved Quality of Care: Computerized notes are consistently more straightforward to examine than a specialist's handwriting. This declines the risk of goofs and misinterpretations that can conversely influence the idea of patient thought. Convenience and Efficiency: Medical and office staff never again need to sit inert managing cumbersome paper records. Customers can get to electronic prosperity records quickly and capably with just two or three strokes on a support. Saving Space: Electronic prosperity records execute the need to store chronicles [6] [7] in monstrous document coordinators, which opens up more space in the work environment for medicinal [8] supplies and gear and various essentials. Patient Access: Many EHR systems fuse a patient passage that empowers patients to see their remedial history and information at whatever point they wish. Money related Incentives: Installing an ensured EHR [5] [9] [10] can empower you to fulfil the meaningful usage and requirements for Medicaid and Medicare, making you qualified for various sparks from the legislature.

Most of the healthcare problems are complex and ambiguous to the doctors and medical experts. Present world is suffering from different kind of diseases and the order of their treatment decreases. Doctors need to go with all the patient data, but it is not being understood by doctors because of its heterogeneous nature.

In order to get knowledge about these kind of heterogeneous data previous literature uses data mining mechanisms. But data mining is not effective in order to give solutions to the heterogeneous data. In order to substantiate that machine learning based auto encoder and convolution neural network (CNN) [3][4] have been used in combination.

The goal of this paper is to provide a high-level introduction into practical machine learning for purposes of medical data classification. In this paper CNN-Auto encoder has been used to extract data from the medical repository and made the classification of heterogeneous medical data.

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* Correspondence Author
F Shaik. Shabbeer*, is a research scholar in College of Engineering & Technology at Acharya Nagarjuna University and he did M. Tech (Computer Science & Engineering) Degree from JNTU-Hyderabad.
Dr. E. Srinivasa Reddy, Professor & Dean R&D in University Engineering College of Acharya Nagarjuna University. Guntur, Andhra Pradesh

During this process the Auto encoder is used to get the prime features and CNN [11] [12] is used for extracting detailed features. Combination of these two mechanisms are more suitable for medical data classification [13] [14] and Hybrid AE-CNN (auto encoder based Convolutional neural network). In the rest of the paper second section gives the details of existing literature, section three explains proposed method, section four illustrates the experimental final section concludes the paper.

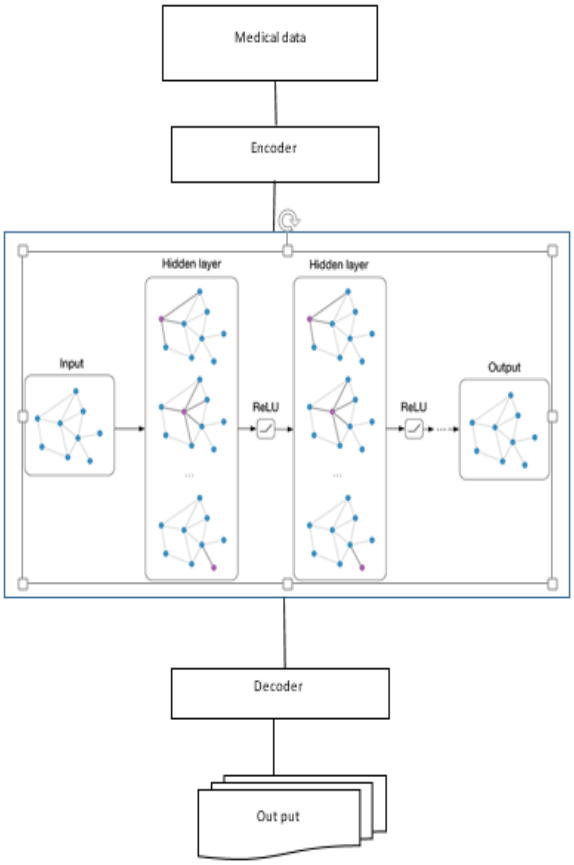

Fig-1: hybrid Auto-Encode and CNN architecture for medical [16] data

II. REVIEW CRITERIA

Kemal Polat et al. [12] examined that determination of hepatitis infection was led with an AI Algorithm. The created AI approach has three phases. In stage one, the component number of hepatitis infection dataset was decreased to 10 from 19 in the element choice sub-program by methods (C 4.5) choice tree inducer calculation. At that point, hepatitis ailment dataset was standardized in the scope of [0, 1] and was weighted with fluffy weighted pre-handling. Thereafter, weighted info esteems got from fluffy weighted pre-handling were arranged by utilizing AIRS classifier framework. In their examination, fluffy weighted pre-handling was connected to hepatitis malady dataset taken from UCI AI database.

Kemal Polat et al. [12] displayed a novel strategy for finding of hepatitis illness. Their strategy depends on a cross breed technique that utilizes highlight choice and fake invulnerable acknowledgment framework (AIRS) with fluffy asset distribution instrument. The AIRS has demonstrated a compelling presentation on a few issues, for example, AI benchmark issues and restorative arrangement issues like bosom disease, diabetes and liver issue. By hybridizing FS and AIRS with fluffy asset portion instrument, a strategy is acquired to take care of this determination issue through arrangement. The heartiness of this technique with respect to testing varieties is inspected utilizing a cross-approval strategy and dataset is taken from UCI AI storehouse. Arrangement precision, affectability and particularity esteems for hepatitis illness dataset were obtained.

Lu, Xinguo et al. [14] portrayed a novel element choice strategy dependent on CFS. At first, the proportions of variable to variable and variable to watch were determined individually. At that point heuristic inquiry strategy to look the space of variable for choosing enlightening quality subset was used and the subset weight was registered utilizing these measures. Through relapse a subset of recognized qualities was acquired. Over a period of time, the stratified testing methodology was exhibited to acquire the most uncovered qualities. The arrangement execution was tried to assess the proposed strategy and Ten-overlap cross-approval test was performed for leukaemia, colon disease and prostate tumour datasets.

E. Caballero Ruiz et al. [16] managed Automatic blood glucose grouping that may assist pros with providing a superior understanding of blood glucose information, got from patient's glucose meter and will contribute in the advancement of choice emotionally supportive networks for gestational diabetes. It displays a programmed blood glucose classifier for gestational diabetes that thinks about six diverse component choice strategies for two AI calculations specifically neural systems and choice trees. Eager, best first and hereditary pursuit calculations were joined with CFS and Wrapper for the component determination and suitably connected.

T. Sridevi et al. [10] built up an element choice calculation Modified Correlation Rough Set Feature Selection (MCRSFS) that predicts both analysis and anticipation when contrasted, and a few information mining arrangement calculations. In their methodology, highlights were chosen based on an unpleasant set with various beginning estimations of decrease in stage one and in stage two highlights were chosen from the diminished set dependent on the CFS.

Yılmaz Kayaa et al. [13] offered another half and half medicinal choice emotionally supportive network dependent on unpleasant set (RS) and outrageous learning machine (ELM) for the conclusion of hepatitis malady. The RS-ELM comprises of two phases. In the introductory stage, repetitive highlights have been expelled from the dataset through RS approach. At that point, order procedure has been executed through ELM by utilizing remaining highlights. The Hepatitis dataset taken from UCI AI vault has been utilized to test the half and half model. The dataset has missing qualities. An expulsion of missing qualities from the informational collection prompts information misfortune, indicating determination has been done in the primary stage without erasing missing qualities.

In the following stage, the characterization procedure has been performed through ELM after the expulsion of missing qualities from sub-highlighted informational collections that were decreased in various measurements and created better arrangement accuracy.

Krzysztof Michalak et al. [11] announced the issue related to high dimensionality of information which is regularly viewed as significant in characterization issues. To bring down information dimensionality, highlight choice techniques are frequently utilized. To choose a lot of highlights that will traverse a portrayal space that is on a par with feasibility for the arrangement task, one must think about potential interdependencies among the highlights. As an exchange off between the multifaceted nature of the determination procedure and the nature of the chosen list of capabilities, a pairwise choice technique off late has been recommended and simultaneously an altered pairwise choice methodology was created. Their exploration recommends that calculation time can be essentially brought down while keeping up the nature of the chose capabilities by utilizing blended univariate and bivariate element assessment dependent on the relationship among the major highlights indicated. Their work introduces the correlation of the presentation of the proposed technique with that of the unmodified pairwise determination system dependent on a few surely understood benchmark sets. The exploratory outcomes demonstrate that, it is conceivable to bring down calculation time and that with high measurable essentialness the nature of the chosen capabilities isn't lowered related with those chosen utilizing the unmodified pairwise determination process.

Pallabi Borah et al. [17] depicted different element choice systems in the field of AI. In their work, a strategy is created namely upgraded correlation based include choice (ECFS) to utilize the component highlight viably and include class relationships to extricate important element subset from multiclass quality articulation information just as AI datasets. The exhibition of ECFS regarding characterization exactness's gotten by choice tree, arbitrary woodland and KNN classifiers has been found exceedingly acceptable when compared to a few benchmark datasets.

M. Dash et al. [22] talked about a far reaching review of many existing strategies from the 1970's to the present and recognized four stages of a normal component choice technique and arranged the distinctive existing techniques as far as age methodology and assessment capacities was concerned. The agent strategies are looked over by every class for point by point clarification and talk by means of model. The authors utilized Benchmark datasets [27] [28] with various qualities. The qualities and shortcomings of various techniques are clarified and given rules for applying highlight choice strategies that are given depending on information types and space attributes. Their study distinguishes the future research regions in highlight determination, acquaints newcomers with this field, and prepares for specialists who look for reasonable techniques for settling space explicit genuine applications.

Imprint A. Lobby et al. [24] expressed that component subset determination can positively affect the exhibition of AI calculations. They portrayed a component subset selector that uses a connection based selector and assesses its viability with three AI calculations named choice tree inducer (C4.5), innocent bayes classifier and an occurrence based student (IB1). The element subset choice gave critical improvement for every one of the three calculations and C 4.5 produced littler choice trees.

Lei Yu et al. [21] presented an idea, dominating relationship and built up a quick channel strategy which can recognize applicable highlights just as repetition among significant highlights without pair insightful connection investigation. Their strategies with productivity and viability are shown through broad examinations with different techniques utilizing true information of high dimensionality.
L.Ladha et al. [20] expressed that element determination is a significant point in information mining, particularly for high dimensional datasets. This work introduces an observational examination of highlight determination techniques and their calculations. In perspective on the considerable number of existing component determination calculations, the need emerges to rely on criteria that empower one to choose satisfactorily, which calculation to use in specific circumstances. This work surveys a few essential calculations found in the writing and evaluates their exhibition in a controlled situation. Xinguo Lu et al. [15] revealed the quality articulation profiles for malignant growth acknowledgment. Be that as it may, the specialists are exasperates by their enormous factors and little perceptions. In their work, a novel element determination strategy dependent on relationship based element choice (CFS) was created. Right off the bat, the proportions of variable to variable and variable to watch were determined individually. At that point heuristic inquiry technique to look the space of variable for choosing useful quality subset and the subset weight was used and later processed. Through relapse they acquired a subset of recognized qualities.

III. PROPOSED WORK

Auto encoders are a different kind of structures in neural networks. These have three layers one is input layer, second one is hidden layer and third one is output layer. Initially after taking the inputs as weights hidden layer update or adjusts the weights by taking the close comparison of input and output as possible and applicable. Hidden layer plays critical role in feature extraction. It only grabs the important features but it may not consider all features, in order to take more accurate feature extraction and get close output as possible.

Auto encoders system that incorporates information layer (i1, i2. . . 1n), shrouded layer (h1 , h2 , . . . , hm), and yield layer (o1 , o2 , . . . , on) whereby the loads of concealed layer speak to highlights of the information medical data.

The setting of auto encoders, which has twofold data practice organizes in particular encoding and deciphering. All through encoding, the inventive info medical data is $I \in [0, 1]p$ At that point we accomplish the shrouded layer h by encoding capacity h = encoder (i)($h \in [0, 1]q$), whereby the encoding capacity is characterized as pursues:

$h = \text{encoder}(I) = g(W \cdot I + b)$.

In the capacity, W ∈ R p×q is the weight network joining information and concealed layers. b ∈ [0, 1]p is the inclination vector, and g is actuation work.

In the last unravelling stage, shrouded layer h is the contribution of the disentangling capacity y = decoder (h) so as to acquire the yield layer o. The deciphering capacity is:

0 = decoder (I) = g W0 · I + b0. (2)

Here, the weight network among shrouded layer and yield layer is W0 ∈ R p×q, and the inclination vector is b0 ∈ [0, 1]q . For the model training process, we let each yield medical data o (j) to be as close in an incentive as conceivable to the first info medical data I (j) . At that point, the article capacity of the model is given by o (j) − I (j).

Since it is anything but difficult to straightforwardly duplicate the info vector to yield vector amid the customary auto encoders' training procedure, the model has second rate execution.

At the point when the test data points and training data points don't meet a similar dissemination, the forecast consequence of the model will diminish drastically [28]. Be that as it may, the Medical data test is high dimensional and their measurements are not free. Along these lines, auto encoders is hard to remove compelling highlights from Medical data. Then again, CNN can see contiguous elements of the medical data (for example nearby recognition) to achieve neighborhood by including responsive field and parameter sharing. This procedure depends on the bit's convolution. Utilizing different convolution bits to develop the example medical data can enable us to acquire an assortment of nearby highlights. In the meantime, the highlights of the model can be diminished by down-testing. In this way, the last highlights of the examined medical data can be removed by iterative convolution and down-testing. Presently auto encoders structure based unsupervised component learning is portrayed as pursued. In the encoder part, includes by CNN are extricated, which always emphasizes various convolution bits', convolution down-testing to decrease the quantity of highlights. At that point, in the decoder part, the extricated highlights to recreate test medical data by de-convolution and up-inspecting was utilized. This implies de-convolution first, and after that emphasize up-examining and deconvolution to re-establish the medical data will be done.

A combination model dependent on the profound convolution system and auto encoders-based (AE-CNN was shown. The model basically has two phases: 1) The encoder organize has test input, convolution layer, pooling layer (down-inspecting layer), reshape task, full association layer, and the component coding; 2) The decoder arrange incorporates highlight coding input, full association layer, reshape activity, deconvolution layer, up-examining layer and the remaking tests. The accompanying presents a particular portrayal of each layer of the model, except that we input a one-measurement medical data into the model. Give x a chance to speak to the information data, and the convolution layer is the component extractor. It utilizes various convolution pieces to perform convolution count of x (numerous convolution bits see x locally), in order to achieve more element maps, which can keep up the primary segments of the info tests. The k-th point included in the map for fmk in the convolution layer is determined as below:

fmk = g (w_ck ∗ x + b_ck). (4)

In the k-th convolution bit of the convolution layer, w_ck and b_ck speak to channels and predispositions of the convolution bit, and ∗ is convolution calculation. The pooling layer is a down-testing process, which tests upper layer's component maps to acquire pooled highlight maps for diminishing data measurement. The pooling activity utilizes a window of length l to permit sliding and extraction of the example include maps. Each examining interim does not cover one another, and the greatest incentive inside the window to get the pooled highlight maps is tested. The figuring procedure is as per the following equation:

pmk = Maxpooling (fmk , l). (5).

IV. RESULTS AND DISCUSSIONS

In this experimental study, medical data from MIMIC3 data set was used and all the experiments are performed with the UBUNTU 16.04 LTS and Intel(R) CPU 2.13GHz, 8 GB RAM and 500 GB HDD. In this work, we utilize MIMIC-III (Medical Information Mart for Intensive Care III) [22] as the necessary information. This dataset contains wellbeing related data for more than 45,000 de-recognized patients who remained in the basic consideration units of the Beth Israel Deaconess Medical Centre somewhere in the range of 2001 and 2012.

Mirror III contains data about patient socioeconomics, hourly essential sign estimations, research centre test outcomes, methods, drugs, parental figure notes and imaging reports. The examination uses records from an accumulation of patients, each being a multivariate time arrangement comprising of 19 factors from fundamental sign estimations (6) and lab occasions (13). Vital signs include heart rate, blood pressure, temperature, respiratory rate, and oxygen and different lab measures of the patients.

Fig-2 shows the accuracy of predicted length of stay in ICU with 12-hours data by varying the number of data samples of 12-hours data. Here we initially consider 2K patients data and goes on increasing up to 12K.

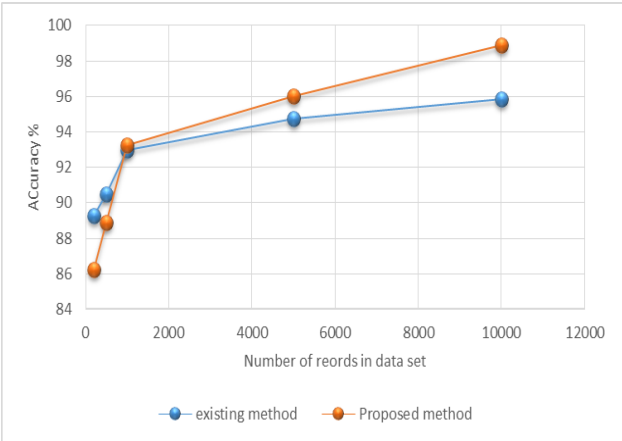

Fig-2: Accuracy of predicting length of stay in ICU with 12-hours data

The comparative results show the accuracy of proposed Hybrid AE-CNN with existing work. The proposed AE-CNN initially shows low accuracy because of less training samples but after increasing data samples it produces more accuracy.

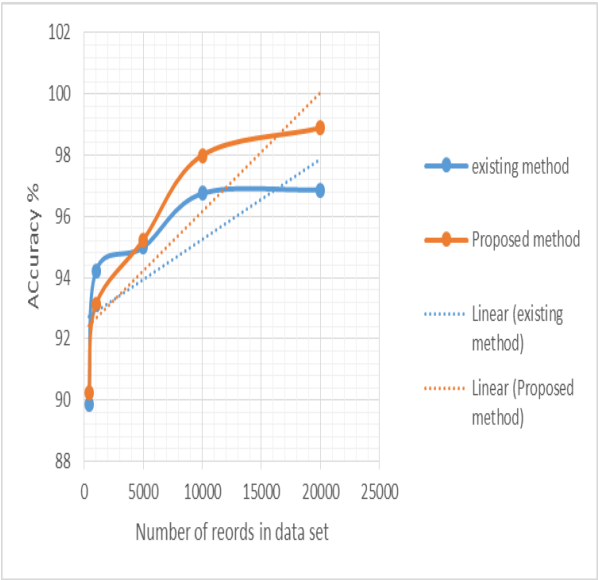

Fig-3: Accuracy of predicting length of stay in ICU with 24-hours data

Fig-3 shows the accuracy of predicting length of stay in ICU with 24-hours data by varying the number of data samples of 12-hours data. Initially 5K patient's data was considered and goes was increased up to 25K. The comparative results show the accuracy of proposed Hybrid AE-CNN with existing work. The proposed AE-CNN initially shows low accuracy because of less training samples but after increasing the data samples it produces more accuracy.

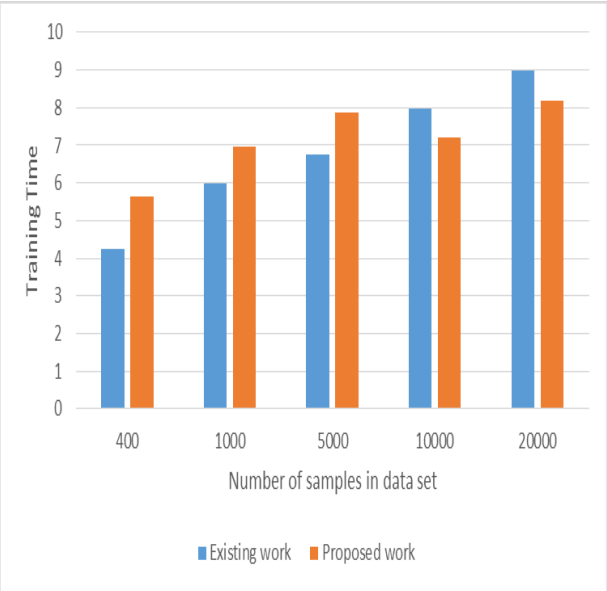

Fig-4: Training time

Fig-4: shows the time for training model with respect to size of the data and the graph shows the time comparison between proposed and existing method. When the size of the data set grows time for training also increased.

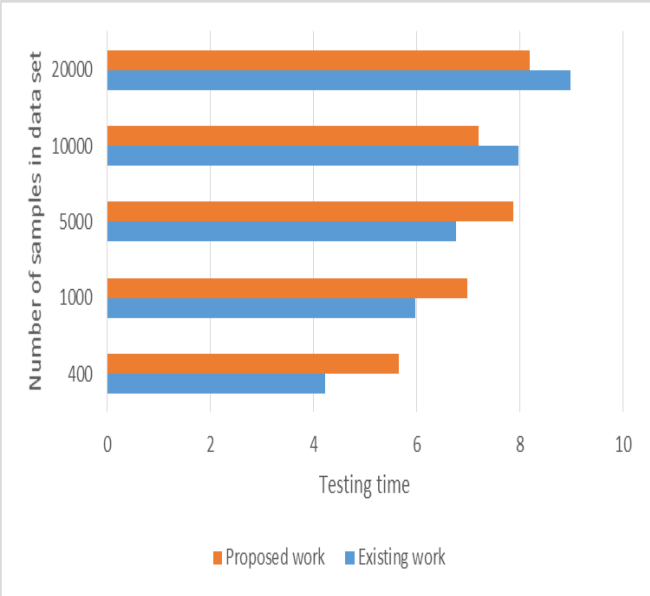

Fig-5: Testing time comparison

Fig-5: shows the time for testing model with respect to size of the data and the graph shows the time comparison between proposed and existing method. When the size of the data set grows time for testing also increased.

Fig-6 shows the length of stay in ICU with 24-hours data samples varying from 2K samples to 12K.

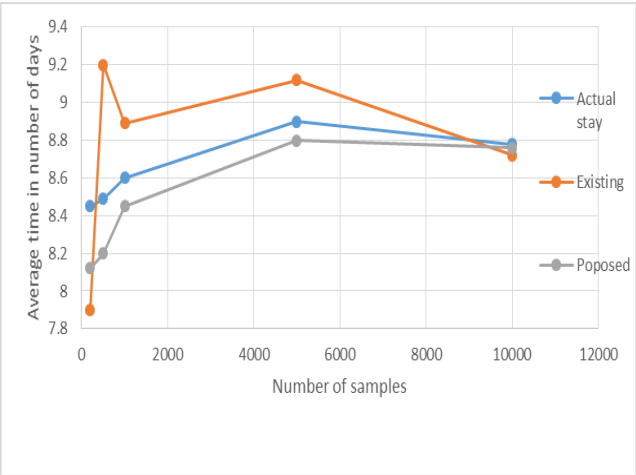

Fig-6: Length of stay in ICU with 24-hours data

The time of stay is taken as average number of days and comparison is made among actual patient stay as per the hospital records and the predictive stay with respect to existing and proposed mechanism. It was observed that the proposed mechanism is more near to the actual.

V. CONCLUSION

In the proposed paper a hybrid mechanism based on auto-encoder and CNN algorithm for medical data classification has been proposed. The proposed mechanism is used to classify all kinds of medical data features. Auto-encoder is utilized to get the generalized features of medical data for instant knowledge was considered,

The CNN which can extract all the features from the medical data was applied and it was concluded that the combination of these two mechanisms will give optimal performance. The MIMIC3 data set for experiments was taken and the features from the ICU data of first 12 hours and 24 hours to predict the length of the stay in ICU was obtained. The performance results showed that the proposed mechanism is more accurate than the base line method.

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AUTHORS PROFILE

F Shaik. Shabbeer is a research scholar in College of Engineering & Technology at Acharya Nagarjuna University and he did M. Tech (Computer Science & Engineering) Degree from JNTU-Hyderabad. He is very much interested in deep learning based on neural networks, medical data retrieval. .

Dr. E. Srinivasa Reddy, Professor & Dean R&D in University Engineering College of Acharya Nagarjuna University. He did Master of Technology in Computer Science Engineering from sir MokhsagundamVisweswariah University, Bangalore. He also did Mater of Science from Birla Institute of Technological Sciences, Pilani. He did Philosophical Doctorate in Computer Science Engineering from Acharya Nagarjuna University, Guntur. Prof. E. S. Reddy, guided several research scholars of PhD to success. His research areas of interest are in various domains including neural networks.