A Hybrid Frame Work for Classification of Multi Class Medical Data with Deep Learning Based Multi-Layer Perceptron and Naive Bayes Classification Model

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***Abstract*—**The affinity for information investigation techniques in healthcare today is extraordinary in light of the fact that the healthcare segment is inexhaustible with data. Healthcare associations produce and gather vast volumes of data in a blend of text just as images on everyday schedule. Due to the immense measure of data, study and examinations are excessively troublesome. Utilization of information examination strategies can assist us with getting valuable data and regularities through medicinal databases, which can be utilized later on comparative cases to spare lives and furthermore lessen the expense of social insurance administrations with the propelled accumulation of information. In this paper we proposed a half and half casing work for order the text restorative information and image therapeutic information. For that we utilize mixture deep learning methodology in two phases in first stage we do preparing of text information with GloVE and VAE, preparing of image information with Conventional Neural Networks (CNN). After we use combined training with Multilayer Perceptron (MLP) with backpropagation (a managed learning calculation) in the assurance of medicinal task techniques. Here we utilize restorative image information and MIMIC-3 therapeutic text informational collection. And afterward we assess the execution of proposed half breed component with existing CNN and GloVE techniques it creates high exactness of characterization of restorative information.

Keywords*—medicinal data; deep learning methodology; Multilayer Perceptron; Conventional Neural Networks*

I. INTRODUCTION

Health Informatics is a rising field which lay weight on legitimate support of restorative and Health information. This field creates various information on every one of these records utilizing conventional techniques couldn't deliver purpose results productively. It is the sole obligation of human services association to assess every one of the information. Remove the concealed data and settle on powerful demonstrative choices. Medicinal information mining is one of the answers for get clinical learning by breaking down clinical databases. Information mining techniques can separate important learning in therapeutic databases. Found information helps therapeutic experts in settling on compelling demonstrative choices. It additionally encourages medicinal services associations to improve the nature of treatment and increment the survival rate of patients. Viable mining strategies are to be produced for speedy extraction of concealed data in voluminous therapeutic databases. Information mining methods are connected in the accompanying regions of social insurance industry to improve nature of administrations [7]: Identifying High Risk Patients Computer-helped perception framework utilizes information mining procedures in discovering hazard patients, conceivable ailments, master frameworks and recognizing variety in the event of predefined measures. Information mining and model-building arrangement recognizes high Health hazard patients. It gives nursing staff to deal with the strength of patients and forestall medical issues [8]. Organization of Health Services Data mining in Health informatics causes medical clinic the executives to improve its nature of administration. Information mining help medical clinic the board to streamline asset portion and give future arranging techniques. Overseers of clinics settle on loads of basic choices regular. As in any regulatory positions, the nature of these choices straightforwardly relies upon the nature of the data [7]**.** To help medicinal services the executives, information mining applications can be created to all the more likely recognize and track ceaseless infection states and high-chance patients, structure suitable intercessions, and decrease the quantity of clinic confirmations and cases [3]**.** For instance, the chairmen need to know the quantity of staff, the measure of assets, and number of free beds required for an up and coming month. For a viable choice, heads require successful strategies to break down the social insurance dataset containing information about patients conceded previously, assets utilized, work force included, and so forth. Information mining gives powerful systems to directors to foresee the quantity of patients conceded and their estimated staying period in the emergency clinic for the up and coming month [3]**.** Clinical Care Medical history of patients, clinical lab results, medicinal imaging and other content of patients causes doctors to give suggestion for improving Health and analyse the illness. Health informatics enables specialists to have quicker access to progressively proper data, and therefore settle on increasingly ideal choices. For example, a concentrated database of patient records will permit a doctor in a neighbourhood facility to approach all the applicable medicinal records of the patient from anyplace in the nation. Besides, applying information mining methods on the brought together database will give specialists, symptomatic and prescient devices that go past what is clear from the outside of the information. For example, another professional can question for every one of the choices that past experts have made on a comparable case. Also, a prescient model can prompt specialists whether a specific case would be better treated as an outpatient or an inpatient [9]. Medicinal Research Most flow effective uses of information mining in Health informatics are turning into a subfield in therapeutic research. The majority of Health related information are put away in little datasets which are dissipated among medical clinics, different clinical labs and research focuses. In any case, most uses of information mining in clinical and regulatory choice emotionally supportive networks require homogeneous and unified information distribution centres. Then again, information mining techniques can even now be effectively connected on little datasets, which encourages analysts to locate the insightful examples, circumstances and logical results relationship and make expectation [9]. Examination of patient records for a specific sickness by scientists to decide the nearness of any hazard factors in their restorative history could help foresee the event of a similar ailment in different patients. Analysts may recognize another hazard factor that could identify the infection sooner in different patients and take into consideration all the more auspicious mediation [9]**.** Instruction and Training Health informatics teaches new human services experts and trains them. It additionally stays up with the latest with ongoing innovation in drug field. The e-learning of Health informatics is a quickly developing field. Applying information mining strategies to e-learning has developed as of late and gives proposed outcomes [16]**.** Treatment Effectiveness In restorative medicines, information mining applications can be utilized to survey the Health state of patients. It is helpful to identify and analyze the ailments in patients. It takes gathering of different causes, courses of medicines and indications. Along these lines, it improves further medicines [22].

As of late, there are quick endeavours to computerize the techniques to bring and break down the human-explicit social insurance information, surrounding us. Different instruments to gather Health explicit information and examination apparatuses to watch the idea of information dependable of human Health state are by and by. How to bring/record the dependable, high dimensional, complex social insurance information and after that to survey the bits of knowledge/shrouded highlights of this information? It has been a noteworthy test to biomedical information investigators. In present day biomedical research, there are different new information types identified with Health been distinguished which incorporate content, picture designs, sound records, sensor information and other electronic Health records. These information types are getting to be mind boggling in nature. [1-2] Using customary methodologies of information mining and factual investigation, we have to perform two stages as (a) to recover significantly compelling and powerful highlights of recorded information (b) at that point to assemble models for forecasts. As indicated by the perplexing idea of information, we need to manage numerous difficulties and need adequate space learning.

In this paper we are proposed a frame work for medical data classification. Medical data mostly in the form of text and image data. In this paper we evaluate the text and image data using deep learning frame work. For to deal with medical data we use hybrid multilayer perceptron approach based on the type of data. For text notes data we use GloVE and VAE. For to deal with image data we use CNN. Both these analysis we will give input as MLP. MLP training will learn both text patterns and image patterns of medical data and perform efficient classification of patterns from medical data.

II. RELATED WORK

Detection of therapeutic science includes distinguishing the nearness of any sickness from a given set x beam conclusion pictures. A picture is given with a mark related with it of the nearness of malady or not. The preparation dataset is either utilized for scratch learning or exchange learning Scope of Deep learning in restorative picture investigation is utilized with pre tra4ned models. The field advanced from being at first focussed on unsupervised learning. [2][3][4][5] Applied profound conviction arranges and stacked auto encoders to characterize detailed patients of Alzheimer's sickness dependent on cerebrum MRI (attractive reverberation imaging). Creators in [6] utilized CNN with pre prepared models. Creators in [7][8] utilized 3d CNN rather 2d CNN to identify Alzheimer's infection. Creators in [9] utilized CNN engineering to cerebrum distinguished chart identified from MRI DTI (dissemination tensor imaging). CNNs have been appeared to adjust to verifiable restorative picture highlights. The other field of grouping is sore or item order. Around there of restorative science a piece of article is grouped as opposed to the entire item. Creators in [10][11] utilized multi stream CNN models to arrange knob and skin patches, [12] proposed a mix of RNN and CNN for grouping and positioning atomic waterfalls in cut light pictures.

Location includes organ/milestone confinement. It includes parsing of 3d volumes. The profound learning fathoms the 3d parsing by accepting them as symmetrical 2d planes. Creators in [13] settled the parsing issue by preparing three 2d planes and taking crossing point with most noteworthy arrangement rate as the yield. Creators in [14] utilized zone of enthusiasm as the milestone around anatomical locales by characterizing a limited 3d box after 2d parsing of 3d volume information. Therefore confinement from 2d models dependent on profound CNNs has been recognized as the most mainstream procedure to distinguish organs, tourist spots and areas. The field is presently moving for precise localisation with sound outcomes. Repetitive neural systems are indicating extraordinary guarantee of investigation in localisation recorded and multi-dimensional RNNs are having an essential influence in spatial field too. Item or region of intrigue discovery has been one of transcendent tedious issues in manual centers. A ton of research has been done to help such exercises with the intensity of registering and preparing to improve the discovery exactness. Early item identification demonstrate depended on four layered CNN to distinguish and recognize knobs in x-beam pictures [14]. CNN is connected to perform voxel grouping, and afterward some type of in the wake of handling is performed for exact article discovery. Creators in [15] utilized 3d convolutional neural systems to look for small scale seeps in cerebrum MRI. Creators in [16] utilized regulated profound learning for discovery of sores in mammography and knobs in chest radiographs.

Division permits the investigation of therapeutic parameters like shape and volume in cerebrum as well as heart examination. The goal of division is to recognize the arrangement of pixels/voxels that make up the limit or the inside of the region of intrigue. Division has been the most well-known field that has been invariant profound learning systems being connected , including the structure of Unique CNNs known as U-NET by [17].U-net design proposes rise to number of up inspecting and down examining layers. In reasonable preparing situation it implies that a picture can be parsed in a solitary go to give division map. Along these lines entire setting of picture can be considered as opposed to a solitary fix, in fix based CNNs. In spite of the fact that U-net works useful for symmetrical 2d cuts, a 3d show has additionally been proposed called as V-net with target work dependent on bones coefficient. A few papers have been likewise distributed dependent on fix prepared CNNs. Creators in [18] connected sliding window check over electron microscopy symbolism with fix based preparing rather single pass picture parsing. U-net likewise discovers application in sore based division to exploit both nearby and worldwide setting. Procedure in [18] is additionally founded on U-net with here and there examining ways with no skip associations. Specialists in [19] likewise utilized U-net to section white issue cuts in cerebrum MRI with 3d CNN and one skip association among first and layer CNN layer. Class lop-sidedness is the real test in division as most voxels are from areas of not intrigue. This issue is settled from fuse of misfortune capacities. Division being the conspicuous in restorative science investigation has seen custom designs coming to forward custom-made for this reason as it were.

III. PROPOSED WORK

Human beings suffer from diseases globally. Diseases may be common or rare type. The dreadful disease like cancer which proves to be life-altering, life threatening and fatal has been given much importance in this study. The prevention, diagnosis, treatment and cure of the disease have remained most challenging for the medical fraternity. Here, medical data mining plays a key role. The extraction of knowledge from medical data assists medical experts, medical decision support system and in discovery of new drugs. To this end in view, the paper has sought to use machine intelligence and evolutionary computing techniques for designing different classification models to improve the diagnostic speed, accuracy and reliability. The datasets are experimented with various models and algorithms; hybridized them; compared them; to find out suitable solutions both for small and microarray medical datasets. The proposed frame work deal with the data like text and images. The proposed work is carried as follows: initially we take raw medical data set which is text as well as image data and apply the pre-processing on both of them. Pre-processing is meant to for removing the anomalies in data. Here we use pre-processing for text to remove stop words and punchivations. And in image data we used to remove edges and background of images. After pre-processing medical data text data will be given to the GLOVE and VAE training algorithm to learn the text features and for image data we will give images data to CNN. CNN train the image feature. Finally both text and image features are given to Multi-layer perceptron it gets train and make classification using Naïve Baysian classifier for get classes of medical data. The below figure 1 Hybrid architecture for Medical data classification of proposed work.

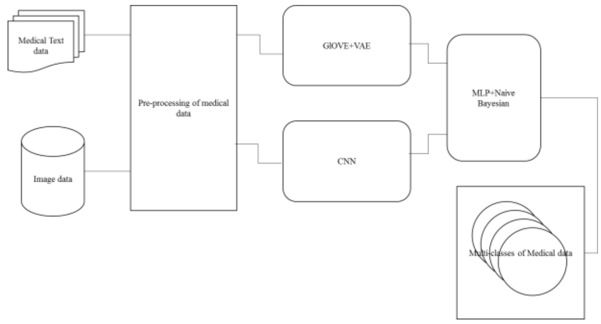


Figure 1: Hybrid architecture for Medical data classification

A. CNN ALGORITHM

Phase I: Conventional Phase
Assign a small value to the all weights and biases
Set learning rate such that 0< ∝ <1
a= one
iterate
for b= one to B do
paradigm xb is distributed along the grid
for d= one to no. of the resultant layer neurons
locate fault
end of loop
for levels O-one to one do
for arrangements y= one to Y do
locate fault factor to propagated backwards
end of for loop
end of for loop
sfor x=one to O do
for y=one to Y do
for all the arrangement weights, y do
find ∆u
renovate weights and biases
u(new)=u(old)+∆u
end of for loop
end of for loop
end of for loop
a = a + one
evaluate MSE1
till MSE1<" ∂" or a > apex limit
Stage II: Knowledge transmit Phase
emphasize
for ts= 1 to TS (new preparing tests)
worldview xts is circulated along the network
for e= one to E
assess result Ce of the convolutional last dimension.

Ce = (C1, C2, C3… . CE)
Discover Cets by utilizing TSL structure
End of for
End of for
Stage III: redesigning loads of learning stage
for trade learning stage
a=one
emphasize
for ts= one to TS
teach the feedforward layers utilizing Cets, GD calculations can be used.
end of for circle
a = a+ one
decide MSE2
till MSE2<" ∂" or a > summit limit.

B. GloVe algorithm

The GloVe algorithm consists of following steps: Collect word co-event insights in a type of word co-event matrix XX. Every component XijXij of such lattice speaks to how frequently word I shows up in setting of word j. typically we filter our corpus in the accompanying way: for each term we search for setting terms inside some territory characterized by a window estimate before the term and a window measure after the term. Additionally we give less weight for progressively far off words, more often than not utilizing this recipe:

Decay=1/offset decay=1/offset

Characterize delicate requirements for each word pair:

wTiwj+bi+bj=log(Xij)wiTwj+bi+bj=log(Xij)

Here wiwi - vector for the primary word, wjwj - vector for the setting word, bibi, bjbj are scalar inclinations for the principle and setting words.Define a cost function

J=∑i=1V∑j=1Vf(Xij)(wTiwj+bi+bj−logXij)2J=∑i=1V∑j=1V f(Xij)(wiTwj+bi+bj−log⁡Xij)2

Here ff is a weighting capacity which help us to keep gaining just from incredibly regular word sets. The GloVe creators pick the accompanying capacity:

f(Xij)={(Xijxmax)α1if Xij<XMAXotherwise

C. Denoising auto encoder (SDA)

T The stacked Denoising auto encoder (SDA) is gotten by stacking Denoising Autoencoder for which concealed layers are intended to identify progressively powerful highlights. Encoding and Decoding activities are executed as the fundamental building square of SDA. Each layer is prepared independently to limit remaking mistake. There are two phases in preparing procedure of this system, a layer-wise pre-preparing and tweaking after that. Here preparing is finished utilizing a tainted form of the examples. The encoder first encodes the info and after that it endeavor to disentangle the contribution from this by fixing this defilement done in information. This debasement is done stochastically. The stochastic defilement process [21] comprises in haphazardly setting a portion of the contributions (the same number of as half of them) to zero. Consequently the denoising auto-encoder is attempting to foresee the ruined (for example missing) values from the uncorrupted (i.e., non-missing) values, for haphazardly chosen subsets of missing examples.

In the event that x is the information ie ∈ 40,17

. Encoder takes the information x and encodes it into the shrouded portrayal y, where d and d1 are speaking to separate measurements.

$$y = s(Wx + b)$$

Where s is a non-linearity, for example, the sigmoid. The inert portrayal y, is mapped back (with a decoder) into a recreation z of same shape as x through a comparative change.

$$z = s(W'y + b')$$

W and W' are the loads. The parameters of this model which are improved via preparing are W, W', b, b' utilizing mean remaking mistake. We had taken W' as WT in our tests. Note here that y catches the principle variables of variety in information. The single concealed layer of SDA is prepared to limit the mean squared blunder of that layer

D. Some Common Mistakes

MLP is one of the most frequently used neural network architectures in MDSS (Bishop, 1995; Hand, 1997; Ripley, 1996), and it belongs to the class of supervised neural networks. The multilayer perceptron consists of a network of nodes (processing elements) arranged in layers. A typical MLP network consists of three or more layers of processing nodes: an input layer that receives external inputs, one or more hidden layers, and an output layer which produces the classification results shows in below figure. Note that unlike other layers, no computation is involved in the input layer. The principle of the network is that when data are presented at the input layer, the network nodes perform calculations in the successive layers until an output value is obtained at each of the output nodes. This output signal should be able to indicate the appropriate class for the input data. That is, one can expect to have a high output value on the correct class node and low output values on all the rest.

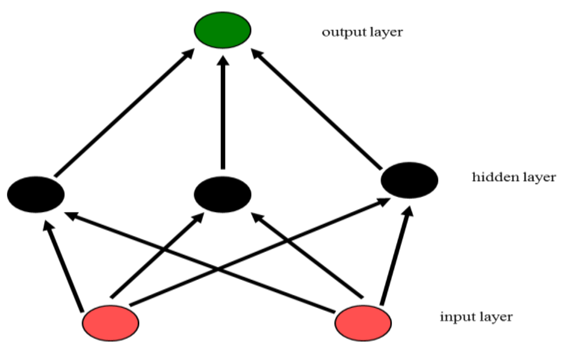


Figure 2: MLP network

Training-Rule for Weights to the Output Layer

$E^p[w_{ij}] = ½ \Sigma_j (t_j^p-y_j^p)^2$

$\partial E^p/\partial w_{ji} = \partial/\partial w_{ji}\ ½\ S_j (t_j^p-y_j^p)^2$

$= \ldots$

$= - y_j^p(1-y^p_j)(t^p_j-y^p_j)\ x_i^p$

$\Delta w_{ji} = a\ y_j^p(1-y_j^p) (t^p_j-y_j^p)\ x_i^p$

$= a\ d_j^p\ x_i^p$

with $d_j^p := y_j^p(1-y_j^p) (t^p_j-y_j^p)$

Training-Rule for Weights to the Hidden Layer

Credit assignment problem: No target values t for hidden layer units.

Error for hidden units?

$d_k = S_j\ w_{jk}\ d_j\ y_j\ (1-y_j)$

$\Delta w_{ki} = a\ x_k^p(1-x_k^p)\ d_k^p\ x_i^p$

Training-Rule for Weights to the Hidden Layer

$E^p[w_{ki}] = ½ \Sigma_j (t_j^p-y_j^p)^2$

$\partial E^p/\partial w_{ki} = \partial/\partial w_{ki}\ ½\ S_j (t_j^p-y_j^p)^2$

$=\partial/\partial w_{ki}\ ½S_j (t_j^p-s(S_k w_{jk}\ x_k^p))^2$

$=\partial/\partial w_{ki}\ ½S_j (t_j^p-s(S_k w_{jk}\ s(S_i w_{ki}\ x_i^p)))^2$

$= -\Sigma_j (t_j^p-y_j^p)\ s'_j(a)\ w_{jk}\ s'_k(a)\ x_i^p$

$= -\Sigma_j\ d_j\ w_{jk}\ s'_k(a)\ x_i^p$

$= -\Sigma_j\ d_j\ w_{jk}\ x_k\ (1-x_k)\ x_i^p$

$\Delta w_{ki} = a\ d_k\ x_i^p$

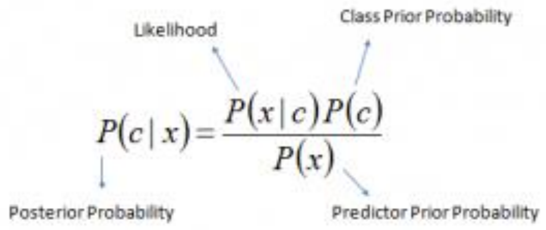
with $d_k = \Sigma_j\ d_j\ w_{jk}\ x_k(1-x_k)$

Backpropagation Algorithm

- Initialize each w_i to some small random value
- Until the termination condition is met, Do
  - For each training example <($x_1,\ldots x_n$),t> Do
    - Input the instance ($x_1,\ldots,x_n$) to the network and compute the network outputs y_k
    - For each output unit k
      - $\delta_k=y_k(1-y_k)(t_k-y_k)$
    - For each hidden unit h
      - $\delta_h=y_h(1-y_h)\ \Sigma_k\ w_{h,k}\ \delta_k$
    - For each network weight $w_{i,j}$ Do
    - $w_{i,j}=w_{i,j}+\Delta w_{i,j}$ where
    - $\Delta w_{i,j}= \eta\ \delta_j\ x_{i,j}$

E. Naive bayes Classification

Naive Bayes model is anything but difficult to fabricate and especially valuable for expansive informational collections. Alongside effortlessness, Naive Bayes is known to beat even exceedingly refined grouping strategies. Bayes theorem provides a way of calculating posterior probability P(c|x) from P(c), P(x) and P(x|c). Look at the equation below:



$$P(c \mid X) = P(x_1 \mid c) \times P(x_2 \mid c) \times \cdots \times P(x_n \mid c) \times P(c)$$

IV. EXPERIMENTAL SECTION

For to perform experimental analysis we use python libraries of keras, tensor flow, numpy, matplot lib…etc. And we used 16GB RAM and 500 GB HDD with 2 GB graphic card and intel I5 processor. As a platform we used UBUNTU 16.04 LTE. And the data set we used here is MIMIC-III. MIMIC III is a vast, openly accessible database containing de-recognized wellbeing related information related with roughly sixty thousand confirmations of patients who remained in basic consideration units of the Beth Israel Deaconess Medical Centre somewhere in the range of 2001 and 2012. The database incorporates data, for example, socioeconomics, crucial sign estimations made at the bedside (~1 information point every hour), lab test results, systems, meds, medical attendant and doctor notes, imaging reports, and out-of-clinic mortality. Impersonate underpins a differing scope of expository investigations traversing the study of disease transmission, clinical choice guideline improvement, and electronic instrument advancement. It is striking for three variables:

It is openly and uninhibitedly accessible.

It includes a various and exceptionally expansive populace of ICU patients.

It contains high transient goals information including lab results, electronic documentation, and bedside screen patterns and waveforms.

Classes of data	Description
Billing	Coded data recorded primarily for billing and administrative purposes. Includes Current Procedural Terminology (CPT) codes, Diagnosis-Related Group (DRG) codes, and International Classification of Diseases (ICD) codes.
Descriptive	Demographic detail, admission and discharge times, and dates of death.
Dictionary	Look-up tables for cross referencing concept identifiers (for example, International Classification of Diseases (ICD) codes) with associated labels.
Interventions	Procedures such as dialysis, imaging studies, and placement of lines.
Laboratory	Blood chemistry, haematology, urine analysis, and microbiology test results.

Medications	Administration records of intravenous medications and medication orders
Notes	Free text notes such as provider progress notes and hospital discharge summaries.
Physiologic	Nurse vitrified vital signs.. Approximately hourly (e.g., heart rate, blood pressure, respiratory rate).
Reports	Free text reports of electrocardiogram and imaging studies.

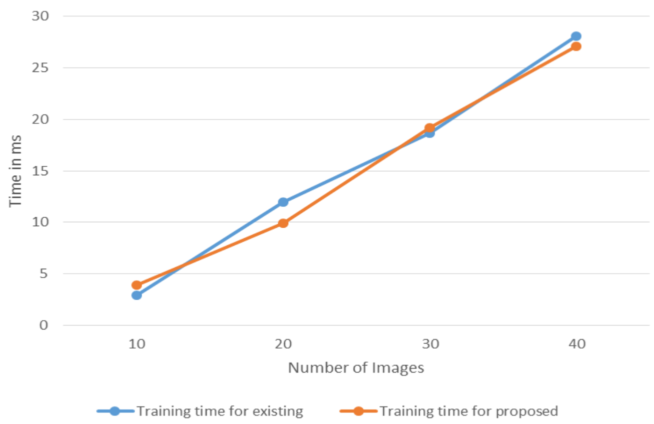


Figure 3: Computation time for training image data to deep learning model

Here figure-3 shows that computation time for training image data set by varying number of medical images for existing work and proposed work. Figure shows the varying of computation time here we use CNN for training. While increasing the number of input images it gets more knowledge about but it need more processing time.

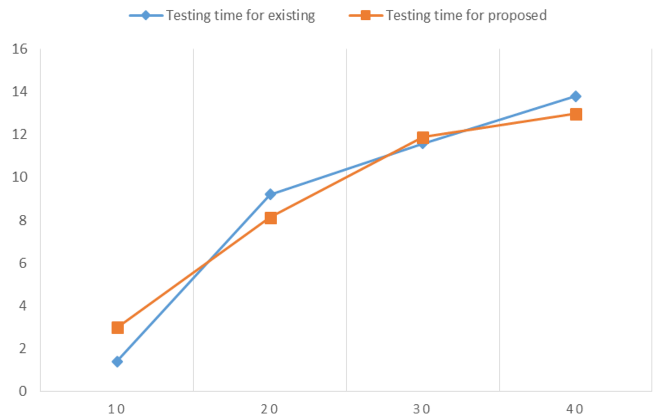


Figure 4: Computation time for Image data testing

Here figure-4 shows that computation time for testing image data set by varying number of medical images for existing work and proposed work. Figure shows the varying of computation time here we use CNN for training and testing. While increasing the number of input images it gets more knowledge about but it need more processing time.

Figure 5: Computation time for training deep learning model EHR data

Here figure-5 shows that computation time for training text data set by varying number of medical notes for existing work and proposed work. Figure shows the varying of computation time here we use GLOVE and VAE for training. While increasing the number of input images it gets more knowledge about but it need more processing time.

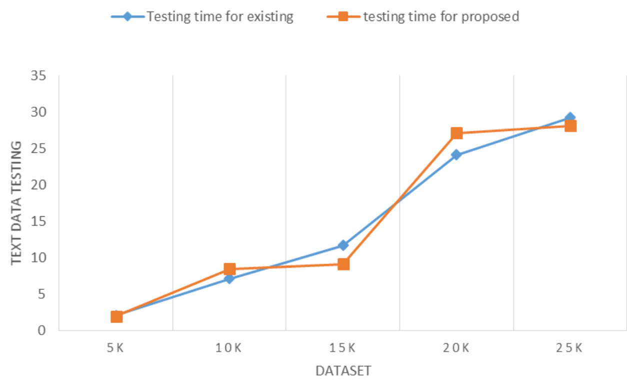


Figure 6: Computation time for training deep learning model HER data

Here figure-6 shows that computation time for testing text data set by varying number of medical notes for existing work and proposed work. Figure shows the varying of computation time here we use GLOVE and VAE for training. While increasing the number of input images it gets more knowledge about but it need more processing time.

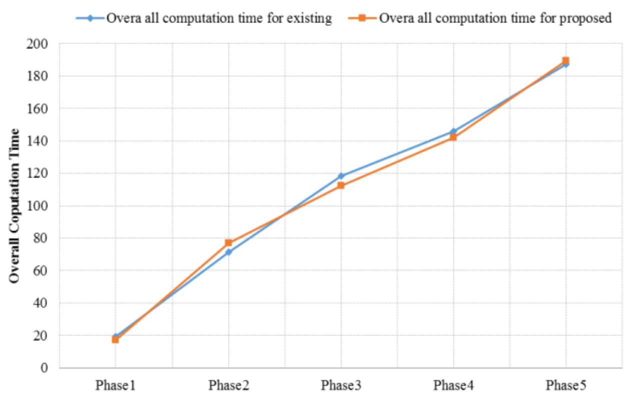


Figure 7: Total computation time

Here figure-7 shows that total computation time for training, testing text data and image data set by varying number of medical notes for existing work and proposed work. Figure shows the varying of computation time here we use GLOVE plus VAE for medical text notes and CNN for image data both these are again gets training using Multi-layer perceptron. While increasing the number of input images it gets more knowledge about but it need more processing time.

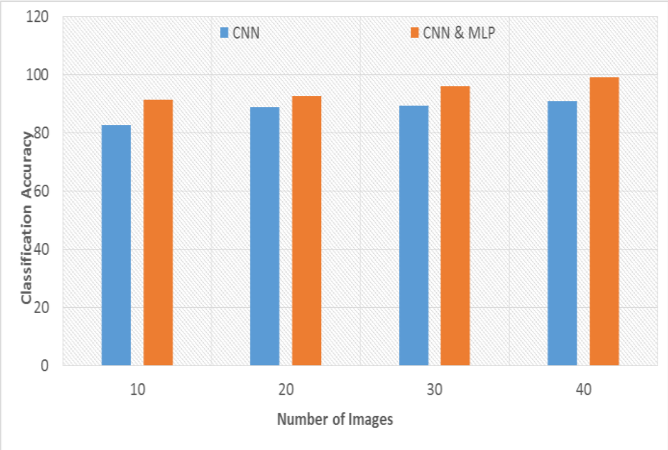


Figure 8: Classification accuracy for medical image data

Here figure-8 shows that classification accuracy CNN and CNN with MLP models with respect data set by varying number of medical images for existing CNN and proposed CNN with MLP While increasing the number of input images it gets more knowledge about but it need more processing time. But while increasing the number of input data it get more knowledge about the data. So it gives more accuracy when compared to existing.

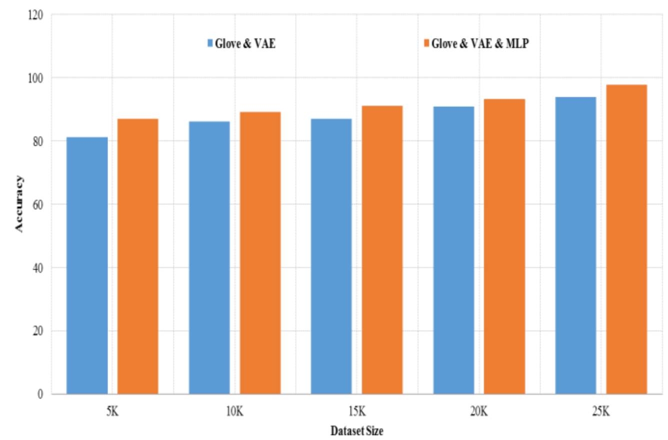


Figure 9: Classification accuracy for HER data

Here figure-9 shows that classification accuracy GloVE plus VAE and GloVE plus VAE with MLP models with respect data set by varying number of medical text notes for existing GloVE plus VAE and proposed GloVE plus VAE with MLP While increasing the number of input images it gets more knowledge about but it need more processing time. But while increasing the number of input data it get more knowledge about the data. So it gives more accuracy when compared to existing.

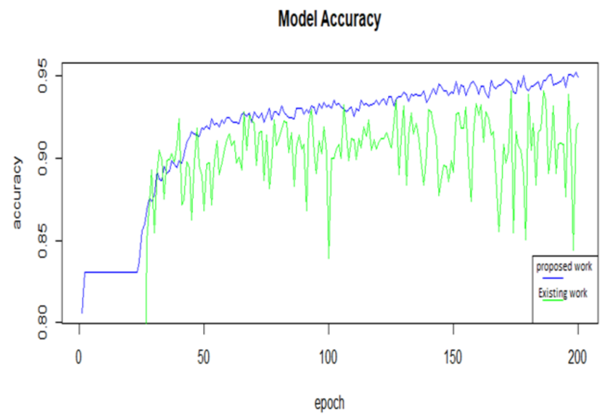


Figure 10: Model Classification accuracy

Here figure-10 shows that classification accuracy for complete frame work with respect data set by varying number of medical images as well as medical text records for existing and proposed models with MLP While increasing the number of input images it gets more knowledge about but it need more processing time. But while increasing the number of input data it get more knowledge about the data. So it gives more accuracy when compared to existing.

CONCLUSION

In this paper we proposed a half and half casing work for order the text restorative information and image therapeutic information. For that we utilize mixture deep learning methodology in two phases in first stage we do preparing of text information with GloVE and VAE, preparing of image information with CNN. After we use combined traing with Multilayer Perceptron (MLP) with backpropagation (a managed learning calculation) in the assurance of medicinal task techniques. Here we utilize restorative image information and MIMIC-3 medical text data. The experimental results shows that the proposed frame work better compared to existing CNN and GloVE methods it produces high accuracy of classification of medical data.

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