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A Machine Learning Model for Clinical Decision Support for Drug Recommendation

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ABSTRACT- Modern machine learning techniques plays a very crucial role in dealing with very complex unstructured data that is available in the medical domain. The wide range of applications in this area is capable of changing the available data to valuable information that could be used for recommendation of appropriate treatment and drugs by analysing the symptoms and other information regarding the patient . In this work, the data available in the form of plain text in the form of electronic health records were used to give appropriate recommendation regarding the medication that could be given to the patient. Thus it acts as a clinical decision support system that can assist the doctor in taking suitable decisions regarding the treatment plan of the patient. The model used techniques from Natural Language processing and Deep Learning to process that raw data and build a learning model for recommendation. The model was able to give an accuracy of 77 percent with raw text as input.

KEYWORDS- Clinical Decision Support System , Electronic Health Record(EHR), Long Short Term Memory(LSTM), Machine Learning , Natural Language Processing, , Recurrent Neural Networks (RNN).

I. INTRODUCTION

The Medical domain generates an enormous amount of digital data in the form of clinical reports which are in both structured and semi-structured form. Considering the huge quantity of biological and clinical data being generated daily throughout the globe which encompasses a lot of useful information, there is a requirement for computational models and techniques for the analysis of that kind of data. For this purpose, Machine learning techniques , with the help of natural language processing is widely being employed that enables the extraction of hidden useful relationships from great volumes of data[1].

Clinical decision support system are computerized healthcare systems which is capable of providing aid or assistance to medical staff, clinicians or the patients themselves for the betterment of health and healthcare services. Among all the kinds of Decision support systems, clinical decision support systems (CDSS) are one of the most challenging and complex decision support systems. This is primarily due to the several attributes that are non measurable and measurable which are decisive in making a decision and the relations that is existent between those attributes which are complex in nature. The attributes include the patient's lifestyles, historical health records, demography, vital statistics, diagnostic reports etc. Deep Learning algorithms are able to act as an effective tool to support the process of decision making. They are proficient in discovery of complex structures that are a part of high-dimensional data .

Deep learning algorithms are a class of machine learning algorithms that are capable of extracting features directly from a collection of raw input provided to the model with the help of hidden layers without the need for intervention of humans. Recently, in the past decade, the deep learning algorithms has been able to catch the attention of researchers because of its encouraging and robust results throughout a wide variety of domains and tasks. Researches show that approaches like CNNs , RNNs etc is able to provide a performance that is better than the other machine learning algorithms and can perform well and attain robust results under different circumstances and given different data structures .In the area of healthcare, convolutional neural network based approaches have been used commonly to work with radiology images, but in the case of text-based clinical notes, recurrent neural networks are more widely used[2].

Out of all the data that an electronic health record consists of, plain text-based clinical notes are one of the most significant ones. But physicians, nurses, other medical staff and pharmacists include data in each segment separately using diverse representations and medical terminology. This is a challenge and had crated complications for the alignment of information. It is a tedious and time consuming process to make an alignment of these information in the clinical profiles and creating a pipeline for these electronic health record notes processing, embedding ,extraction of clinical terms and aligning across other units of healthcare providers. Hence , the current task of EHR related systems is to improve the efficiency so as to empower the physicians with more user friendly and efficient systems. In addition, such systems should assist in bringing down the costs associated with clinical diagnostics and minimalizing the possibility of medical errors.

The initial works on EHR analysis used simpler and traditional statistical methods. In the recent years , more advanced machine learning techniques like SVM(support vector machines), random forest ,logistic regression and Cox proportional hazard model have been employed in combination with natural language processing techniques for extracting reliable predictive from the EHR data . The simpler methods were weak in dealing with high-dimensional input and they require hand-crafted features or markers. To ease these issues, modern machine learning methods were introduced.[3] [4]

II. LITERATURE REVIEW

Chalapathy et al. [5] suggest a method that is based on Recurrent Neural Networks(RNNS) with bi-directional long short-term memory model and CRF (conditional random field) decoding for the generation of word embeddings like Word2Vec and GloVe andWord2Vec . To practice concept representation and extraction, in this model each word in a sentence is mapped to a random word embedded vector initially. After this stage, the model makes use of word-embedding training methods of CBOW ,Skip_Gram and GloVe and for the learning of entire data collection for the generation of the representation of vectors .

The work done by Mei et al. [6] takes as input, the plain text data from the EHR system for the construction of their proposed "Deep Diabetologist" model using Recurrent neural Networks for sequential data modelling using EHR. Their study aims at generation of personalised clinical predictions on hypoglycaemia medications meant for patients with diabetes. The pre-processing of data was performed by mapping the patient IDs and the corresponding event IDs. Then the recurrent neural network(RNN) based medication recommendation model is used for the generation of relevant probabilities, which was followed by a hierarchical model based on RNN to follow the time steps.

Choi et al. [7] suggested an approach that is data driven in order to leverage clinical data in the form of EHR directly for the purpose of medical concept learning. Specifically, the technique was able to map the clinical concepts to related concept vectors which are related to each other that depends on temporal co-occurrence relationships within the plain data inputs. Further, the model was used to transform a patient's clinical and biological data in EHR system that are quite heterogeneous to clinically meaningful features. Thus, the patient vectors are modelled parallel from the clinical concept vectors that are related . Subsequently, the proposed model was able to generate patient representation by making use of learning representation of clinical concepts.

Another work was proposed by Liang et al. [8] that use a convolutional deep belief network for the training of the EMR data to enable the support of clinical decision making. The researchers used dataset of hypertension that was retrieved from HIS system, combined with data from Chinese medical diagnosis and prescriptions of treatment manually converted EHR systems. The outcome of this experiment were capable of performing considerably superior to the conventional shallow models in extracting the previously unidentified hidden medical relations and concepts.

The work done by Grapov et al. [9]suggests that the different deep learning techniques at different levels of clustering and classification of bioinformatics and genomic based system is capable of personalizing the impact and effects of various drugs and treatment plans for patients so that the quality of medical recommendation system could be improved. This specific framework for precision medicine that is modelled using deep learning techniques may play a crucial role in prescribing appropriate medicine for more efficient treatment of patients. The research [10] on medical records developed a Deepcare system based on Neural Networks used present records of patients, their previous medical history and existing and upcoming state of patients. The model used Long-ShortTerm-Memory (LSTM) to maintain and analyze the details of the patients in the memory. It achieved an accuracy of 75.4 % when made use for mental-health records of patients.

III. METHODOLOGY

The methodology proposed uses deep learning based architecture that is modelled by stacking several layers of simple modules hierarchically. The modules perform nonlinear operations to compute representations for every layer from the previous layer. Every layer in the stack is also performs transformation of the input to improve the sensibility and invariance of the representation. It uses a hybrid model of RNN and LSTM in combination with NLP techniques.

The data used for building the model was obtained from i2b2 dataset . De-identified Electronic Health records in the form of raw text was used for training the model. The dataset consisted of 1580 EHR documents which consisted of patient information like symptoms , medication , vital statistics and treatment/medication recommended. The data is stored in the MongoDB database and fetched one – by – one for processing. The stored raw data is in json format . The first phase involves usage of Clinical Named Entity Recognition facilitated by pre-trained silver Calcomp raster file model in i2b2 format. A concept file is generated which identifies the problem, treatment and test along with the time-stamp as shown in the Figure 1 below:

```
c="shortness of breath" 12:35 12:37||t="problem"
c="exertion, some shortness of breath" 12:39 12:43||t="problem"
c="nebulizer treatment." 12:52 12:53||t="treatment"
c="pulmonary function tests" 15:4 15:6||t="test"
c="bronchodilator treatment" 17:9 17:10||t="treatment"
c="steroid taper" 17:47 17:48||t="treatment"
```

Figure 1: A Sample Generated Concept file

The Pre-processing was done on the text which is now in the form of the concept file. Tokenization, noise removal and stop-word removal was performed on the raw text to eliminate irrelevant terms. To identify named entities in the text, Bi-directional LSTM-CRF method was employed. The data is vectorized and label is applied to the identified words. Here , a Recurrent Neural Network is combined with LSTM model to obtain more efficient results.

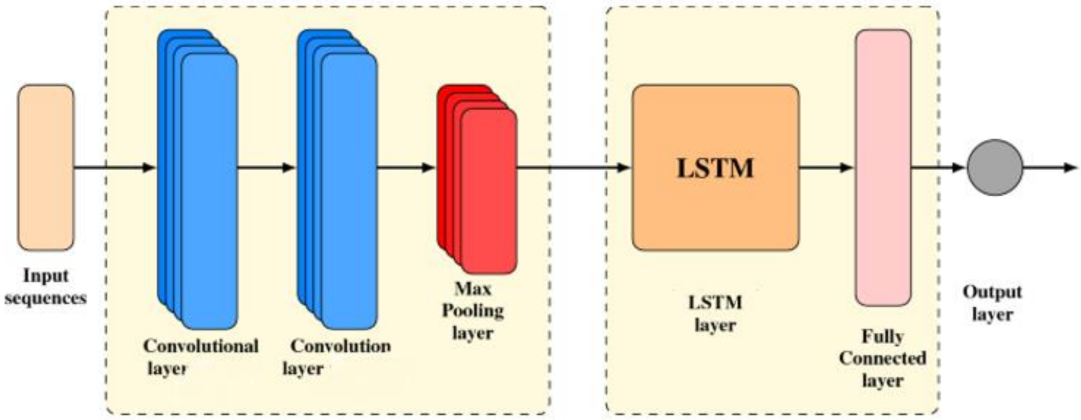

Figure 2: Architecture of Convolutional Layers and LSTM Layer

RNNs and LSTM : RNNs are different from the rest of the other feed-forward networks due to the presence of the cyclical connections . These connections form feedback loops in the hidden layers, and thus allows the historical information to be persistent in the hidden states of the network. Thus RNNs are specifically appropriate for the processing of temporal-related data and makes use of sequential information. But then the capability of vanilla RNNs to process sequence in a long range is limited due to the exploding and vanishing-gradient problems. The individual units in LSTM are able to solve this issue by changing the gate units for determining what information is to be retained in the memory and what is to be removed from memory, given the input value, previous state and the current state of memory. The Architecture is as given in Figure 2. The LSTM technique outshine many other methods at its ability to process long sequential data and is quite effective for the capturing of long-term dependencies. This ability of LSTM is made use of in this model to predict the relevant medication. After the data are input, the features extraction is performed by convolutional layers . Then, the features are input into LSTM for further training(figure 3).[11,12]

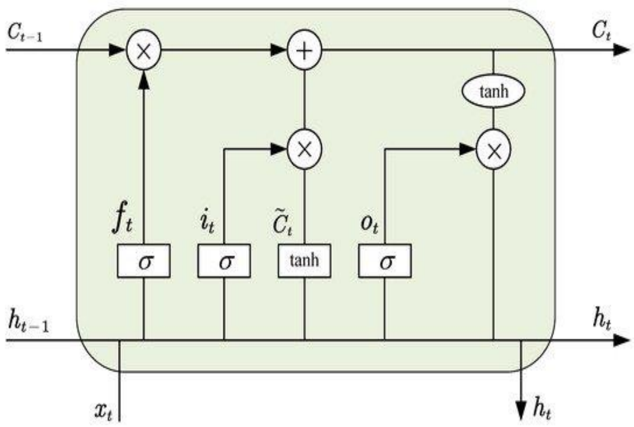

Figure 3: The structure of an LSTM Unit

IV. RESULTS AND PERFORMANCE ANALYSIS

The performance metrics that were used for the model assessment were accuracy,precision,recall and F1-score and is shown in Table 1. Also, sensitivity is thought of as more significant from the clinical perspective, than specificity since it displays how accurately the event was identified .Thus, while comparing several models, specificity was considered more important. The Precision and recall are defined by Equation 1 and Equation 2 respectively , where TP represent true positive, FP represent False positive, FN represent False Negative and TN represent True Negative.

$$\text{Precision}= {TP}/{(TP+FP)} \qquad \text{Eqn(1)}$$

$$\text{Recall}= {TP}/{(TP+FN)} \qquad \text{Eqn(2)}$$

The value of F1 score, considers recall and precision and is the harmonic mean of recall and precision. The higher the values of precision and recall are, the higher is the F1 score that is obtained. It is given by Equation 3

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \text{Eqn (3)}$$

Table 1 : Precision , Recall and F1-score

	Precision	Recall	f1-score
Accuracy			0.77
Macro average	0.77	0.76	0.76
Weighted average	0.78	0.77	0.77

The macro F1 score or macro-averaged F1 score is calculated by finding the arithmetic mean of all the per-class F1 scores. This calculation considers all classes equal irrespective of the values of support. If we calculate the mean of all per-class F1 scores while taking into account each class's support, the weighted-averaged F1 score is obtained. The number of actual occurrences of the class in the dataset is called Support[13].

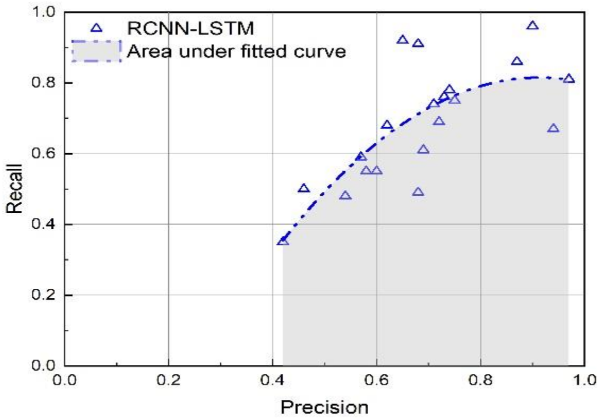

Figure 4: Recall Vs Precision

Similar to ROC curves, the information could be summarized in a precision-recall curve with a single value. [14]. This particular summary metric is known as AUC-PR. It represents area under the precision Vs recall curve (figure 4).

V. CONCLUSION

Modern machine learning systems can contribute much to the medical domain with its capability in dealing with high dimensional data. The work proposed suggests a method using Deep neural network in predicting the medication that could the suggested to a patient based on the information stored in the EHR systems in the form of plain text. Thus it helps in harnessing the information and patterns that is hidden in the text that is otherwise not used much. The techniques from NLP also aids to this method as a way for initial processing of the clinical information.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

REFERENCES

[1] E. H. Houssein, R. E. Mohamed and A. A. Ali, "Machine Learning Techniques for Biomedical Natural Language Processing: A Comprehensive Review," in IEEE Access, vol. 9,pp.140628-140653,2021,
[2] doi: 10.1109/ACCESS.2021.3119621.
[3] Meleet, Merin, G. N. Srinivasan, and Nagaraj G. Cholli. "Entity Recognition in Clinical Text Using A Hybrid Model Based on LSTM and Neural Networks." 2022 4th International Conference on Smart Systems and Inventive Technology (ICSSIT). IEEE, 2022.
[4] Reimer, Andrew P., et al. "Subcategorizing EHR diagnosis codes to improve clinical application of machine learning models." International Journal of Medical Informatics 156 (2021): 104588.
[5] Amitha and Meleet, M, A System for Recommendation of Medication Using Gaussian Naïve Bayes Classifier, IJIRCST Vol-7 Issue-3 Page No-100-103 (ISSN 2347 - 5552)
[6] Chalapathy, Raghavendra, Ehsan Zare Borzeshi, and Massimo Piccardi. "Bidirectional LSTM-CRF for clinical concept extraction." arXiv preprint arXiv:1611.08373 (2016).
[7] Mei, j., Zhao, S., Jin, F., Xia, E., Liu, H., Li, X.: Deep diabetologist: learning to prescribe hypoglycemia medications with hierarchical recurrent neural networks. arXiv. https://arxiv. org/pdf/1810.07692.pdf
[8] Choi, E., Schuetz, A., Steward, W.F., Sun, J.: Medical concept representation learning fromelectronic health records and its application on heart failure prediction. arXiv. https://arxiv.org/abs/1602.03686 (2017)
[9] Liang, Z., Zhang, G., Huang, X., Hu, Q.: Deep learning for healthcare decision making with EMRs. In: Proceedings of 2014 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), pp. 556–559
[10] Grapov D, Fahrmann J, Wanichthanarak K, Khoomrung S. Rise of deep learning for genomic, proteomic, and metabolomic data integration in precision medicine. Omics: a journal of integrative biology. 2018;22:630-6.
[11] Pham T, Tran T, Phung D, Venkatesh S. Predicting healthcare trajectories from medical records: A deep learning approach. Journal of biomedical informatics. 2017;69:218-29.
[12] Guo, Aixia, et al. "Predicting cardiovascular health trajectories in time-series electronic health records with LSTM models." BMC Medical Informatics and Decision Making 21.1 (2021): 1-10.
[13] Rasmy, L., Zhu, J., Li, Z., Hao, X., Tran, H. T., Zhou, Y., ... & Zhi, D. (2021). Simple Recurrent Neural Networks is all we need for clinical events predictions using EHR data. arXiv preprint arXiv:2110.00998.
[14] Takahashi, Kanae, Kouji Yamamoto, Aya Kuchiba, and Tatsuki Koyama. "Confidence interval for micro-averaged F1 and macro-averaged F1 scores." Applied Intelligence 52, no. 5 (2022): 4961-4972.
[15] Carrington, André M., Douglas G. Manuel, Paul W. Fieguth, Tim Ramsay, Venet Osmani, Bernhard Wernly, Carol Bennett et al. "Deep roc analysis and auc as balanced average accuracy to improve model selection, understanding and interpretation." arXiv preprint arXiv:2103.11357 (2021).
[16] Squarcina, Letizia, Filippo Maria Villa, Maria Nobile, Enrico Grisan, and Paolo Brambilla. "Deep learning for the prediction of treatment response in depression." Journal of Affective Disorders 281 (2021): 618-622