Multiple diseases detection using deep learning

Abhinav Saurabh
as6318@srmist.edu.in
Dept. of Computer Science
SRMIST
Chennai, India

Adyasha Sahu
adyasha.98@gmail.com
Dept. of Computer Science
SRMIST
Chennai, India

C. Vijayakumaran
vijayakc@srmist.edu.in
Associate Professor
Dept. of Computer Science
SRMIST
Chennai, India

***Abstract*—Early detection of preventive diseases can play a crucial role in timely intervention and management. It also assists in efficient distribution of resources in the healthcare sector. Many approaches involving various machine learning algorithms have been used. However, clinical-decision machine learning algorithms for medical imaging face challenges with interpretability and reliability.We will use multiple architecture like CNN and other models for detection of disease. We also implement the GRU model that has shown impressive results on smaller datasets.**

We endeavour to develop a system that facilitates early detection of multiple critical diseases using neural networks. We use different datasets for each of the diseases as per the need of the disease. We will present an easy to use GUI framework that allows anyone to access the model easily and derive results.

Index Terms—Machine Learning,DeepLearning,LSTM,CNN

I. Introduction

The previous decade has witnessed a high increase of information in EHR systems. Structured patients data like past diseases, lab conclusions,demographics, medications and procedures, and unstructured data like progress reports and discharge reports are collected at the time of each clinical trial. This gives an opportunity to excavate hidden information and use it to improve the quality of healthcare. Considering the surplus of patients and records, the doctors find it difficult to detect recurring patterns.Medical diagnostics use a large amount of images as analysis data.We can use this data as the basis for automated analysis using advanced algorithms and speed up detection and also reduce load on health professionals. Such a model can also work as an expert system. It can revolutionize the way medical treatments are provided. Machine Learning algorithms are best suited for this purpose and can resolve this problem.

Urban living has had an increasingly detrimental effect on public health. According to a United Nations report, more than half of the humans of the world live in urban regions and it is predicted to increase even more by the mid of the twenty -first century. Given our country's agenda to create smart cities, it is evident that healthcare should be a top priority in this narrative. On this basis smart healthcare systems is the use of intelligent health modules that are connected to each other, ehealth and adoption of wellness policies. The smart city budget of India is some 930 million US dollars. While only 7 percent of this has been allocated to healthcare, only a small portion of the budget has been utilized till date. So there is much scope for increased expenditure in the health sector and additional benefits. This smart city cause can be expanded to improve city life in ways like reducing pollution levels, use of addictive circumstances and harmful food products that are for example high in sugar and lead fats and to chronic diseases. While these real life approaches go a long way in bringing about changes our approach concentrates on data accumulation and algorithmic manipulation. These data are currently being used with increasing frequency to predict future events. While predictive models have been made to calculate needs, most current jobs have focused on specially designed predictive models that predict a limited set of outcomes. However, in everyday clinical trials involves an unscheduled and different mix of scenarios and require different prediction models in the 100s to 1000s. It is not practical to make and deploy specialized models one by one.

II. Problem Statement

A large section of predecessors working in this particular field focus on structured data and lose the novelty of new knowledge that can be mined from unstructured data and thus possible new cases are not identified. In this we make a general framework for disease prediction that combines both free approaches.. We will use multiple architectures like CNN, LSTM and GRU for detection of disease using image analysis. And, we try to compare different types of methods for medical professionals to interpret model prediction accuracy.

III. Literature Survey

The following papers were analyzed and hence skimmed through for reference for this research paper. The brief sum-mary is given here for the papers analyzed

A. Theodora S. Brisimi, Tingting Xu, Taiyao Wang."Predicting chronic disease hospitalizations from Electronic Health Records: An Interpretable Classification approach

This approach uses a joint classification and clustering approach. Clustering is used to find clusters in positive samples. Classification is used to separate positive and negative samples. It uses Linear and Sparse linear SVM for clustering. It uses Linear Regression, Random forests and KLRT for classification. It uses an ACC for alternating between classification and clustering and to achieve convergence. It does clustering of positive samples after classification. It stresses upon the need of finding heart disease and diabetes threat within one year of admittance to reduce risk. It uses electronic health records of patients. It stresses upon alerting doctors to take future action and doesn't give priority to maximize accuracy..

B. Tal Baumel, Jumana Nassour-Kassis." Multi-label Classification of Patient Nodes: A Case Study on ICD code assignment"

This approach focuses on assigning ICD 9 codes to data obtained from MIMIC-II and MIMIC-III clinical datasets. Often a patient record needs to be classified by multiple labels from thousands of ICD9 labels. This method displays four classification approaches namely: SVM one-vs-all model, CBOW, CNN and HA-GRU. From this we find that HA- GRU gives the best performance while preserving text and accommodating full transparency. This is a general model of ICD tagging that uses all ICD codes and hence not for specific implementation.

C. Edward Choi, Mohammad Taha Bahadori."Doctor AI: Predicting Clinical Events via Recurrent Neural Networks

This method leverages data from EHR over a period of eight years for 260K patients to predict medical conditions and uses for subsequent visitations. It is a temporal prediction method that uses RNN on time-stamped data for specifying multiple labels to patient based on the disease. A secondary goal is predicting the time of the next visit for the patient. It uses in adjacent GRUs alongwith RNN due to their improved performance over LSTM. It achieves high prediction accuracy. This method relies on a long term data of patient being available. The problem also arises in knowledge transfer between hospitals. Limitation arises when sometimes incorrect behavior is given importance over correct prediction and this degrades patient health. This mimics an average physician but can do better.

2.1.13 Esteva, Andre & Kuprel, Brett & Novoa, Roberto & Ko, Justin & Swetter, Susan & Blau, Helen & Thrun, Sebastian. (2017). Corrigendum: Dermatologist-level classification of skin cancer with deep neural networks. Nature. 546. 686-686. 10.1038/nature22985.

This project is outfitted with deep neural networks to act as an Artificial Intelligence device that detects skin cancer on par with medical professionals. The idea is to create a mobile device that is loaded with deep neural networks. This method studies skin lesions to detect multiple types of skin cancer.It offers low cost diagnostics.

E. Havaei, Mohammad & Davy, Axel & Warde-Farley, Brain Tumor Segmentation with Deep Neural Networks. Medical Image Analysis. 35. 10.1016/j.media.2016.05.004.

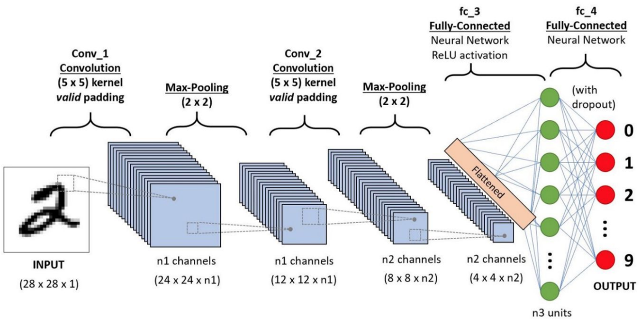
They have utilized a deep convolutional neural network for automated brain tumor segmentation. They have used a two pronged CNN architecture that models both local and global context. They have stacked two CNNs together and used a two phase training method to reduce imbalance of tumor labels. The result is a state of art system that was presented at MICCAI.

F. Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun "Deep Residual Learning for Image Recognition"

This paper works on improving image Recognition in models that have deeper neural networks than others. The work offers a residual learning structure for the neurons to provide higher accuracy and faster results. This is done by restructuring layers that concentrate on inputs as reference rather than unreferenced functions. It is empirically proved that this method performs better on certain standard datasets

IV IMPLEMENTATION

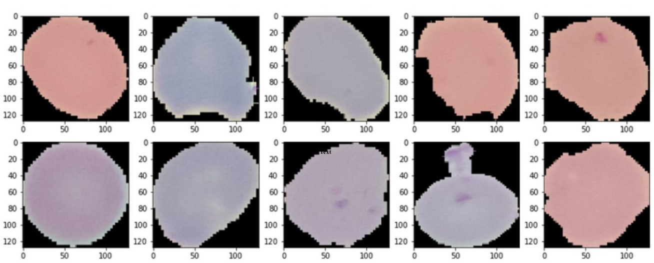
Malaria



How does a typical CNN architecture looks like? This image is taken from Google and it shows a CNN architecture used for recognizing hand written digits using the MNIST dataset.

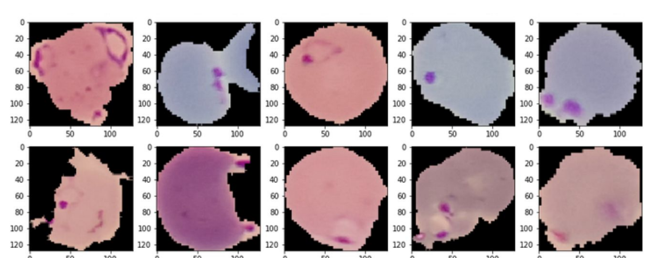
Taken the image of RGB cells input and further apply the above CNN architecture to the to train the model over infected and non-infected cells by malaria. Further model has been trained over 8000 cell images to get the results.

Further steps have used activation functions like Sigmoid and Relu to introduce non-linearity into the neurons.For the purpose of optimization usage of optimizer such as Adam optimizer has been implemented to calculate the present gradients using past gradients.



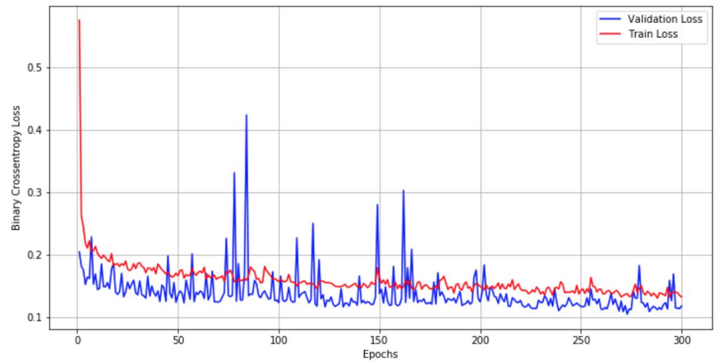
Output showing random sample of cell images which are not infected by Malaria.

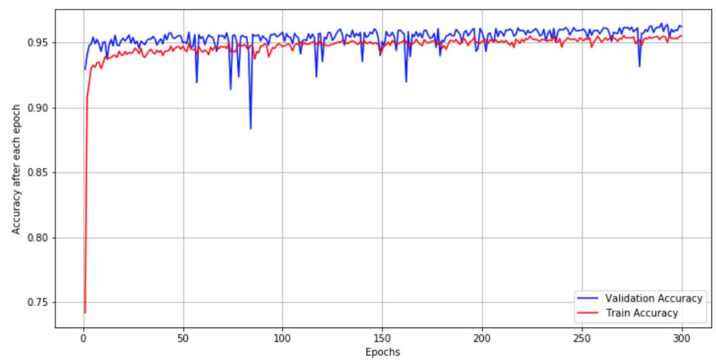
The above picture shows the cells which are not infected by malaria.There aren't any spots in the cells above as can be seen. Using CNN the model is trained to classify them into them into non-infected cells. Further the prediction is made accordingly.



Output showing random sample of cell images which are infected by Malaria.

The above images showing the blunt spots inside the microscopic image of the cells depicts that it has been infected by malaria.When the cell is infected by malaria it depicts distorted blunt cells or blunt spots.The model is trained to train accordingly to identify the spots and classify them as infected.

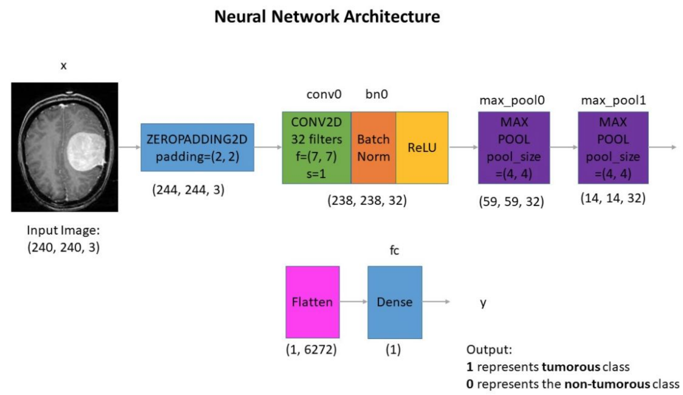




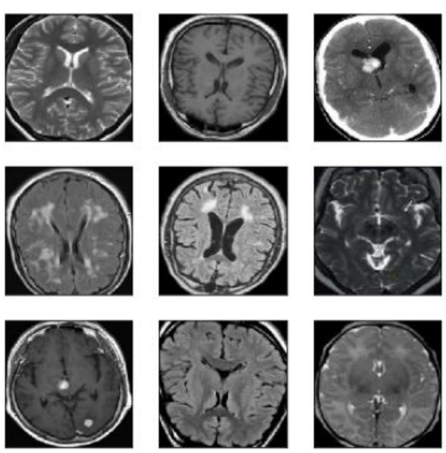
The most accurate model that we have has reached an accuracy of 97.84% on unseen data, with a low false negative value of 29 and an high recall of more than 99% for predicting the infected cells.Using batch Normalization and dropouts has also been good as it helped us to reduce the over-fitting of the model.

Brain Tumour

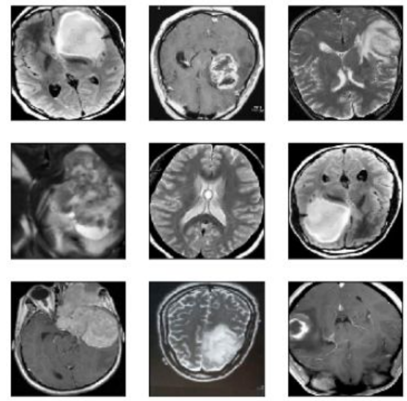
Tumours can appear in any shape ,size or the contrast inside the brain.Our goal is to provide an efficient machine learning solution to exploit the same.



The above architecture is implemented based on convolutional neural networks. The model is trained using datasets of MRI brain scan images of people over various iterations. Brain tumours can appear anywhere in the brain and is a tentacle like structure which needs to be detected.

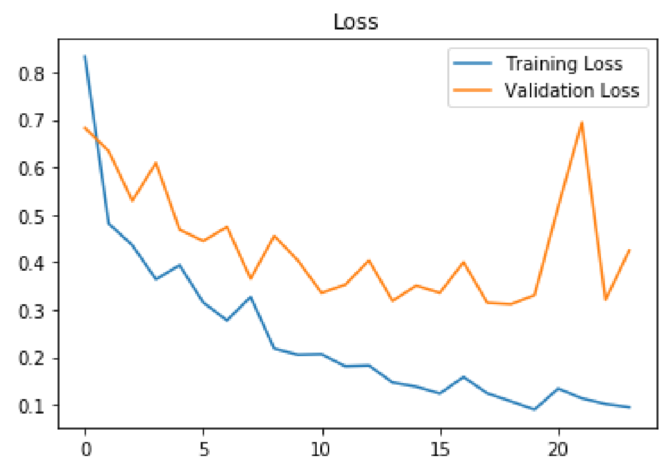


The above image shows various MRI scans of healthy brains that don't have the tumour part in them.We train the model to categorize them into a healthy brain. We use CNN and further batch normalization. Also we use activation functions such as RELU.

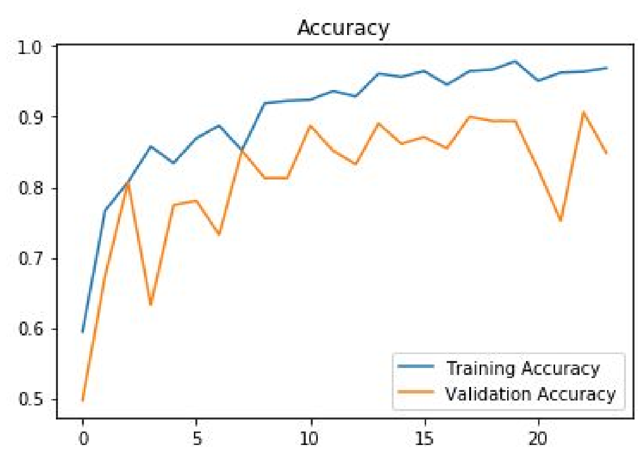


The above image shows MRI scans of brain that have already presence of tumour. Our model is further trained to categorize them into infected category.

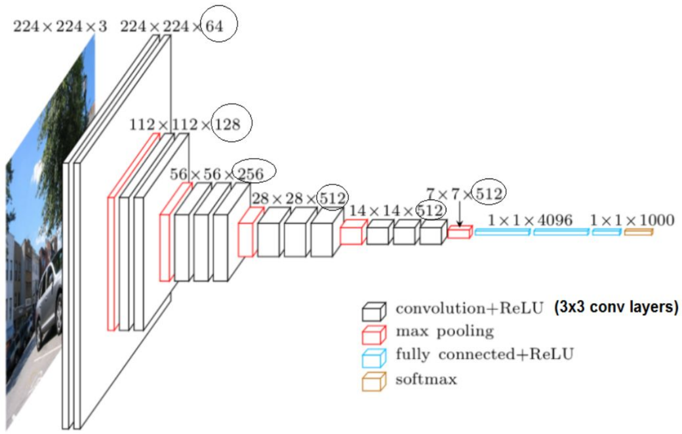
The graph shows the training loss and validation loss for 20 epochs where they are closing in, if we increase the number of epochs we can still decrease the validation loss.



The model is performing well on the validation set and training set where the accuracy is close, we can conclude the model is not overfitting.



RetinalOCT



The above CNN architecture has been implemented to detect the retinal disease in the eye using high resolution retinal images. Here the retinal OCT images will be classified based on convolutional neural network.

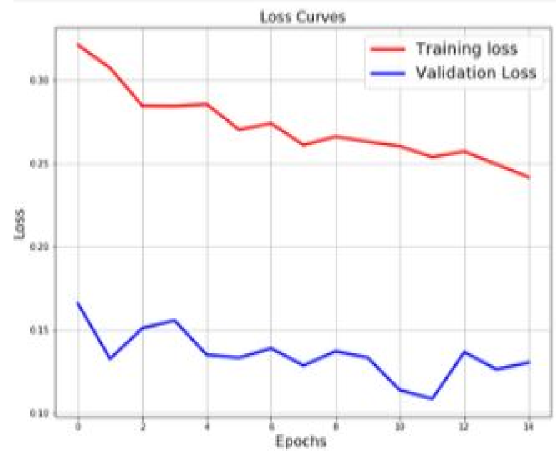
We can diagnose retina damage using image classification. Retina damage can be classified under three categories namely chloroidal neovascularization (CNV), Diabetic Macular Edema (DME) and Drusen.

CNV is a condition in which new blood vessels originate in the chloroid. Chloroid is a layer that contains a network of vessels and is present under the retina. This affects central vision and is one of the major causes of blindness. DME is a complication of diabetes and results from fluid build up in the central part of the eye also known as macula. It is characterized by blurred vision and can eventually lead to loss of eyesight. Drusen are either white or yellow accumulations of extracellular material under the retina or optic nerve and are composed of lipids.

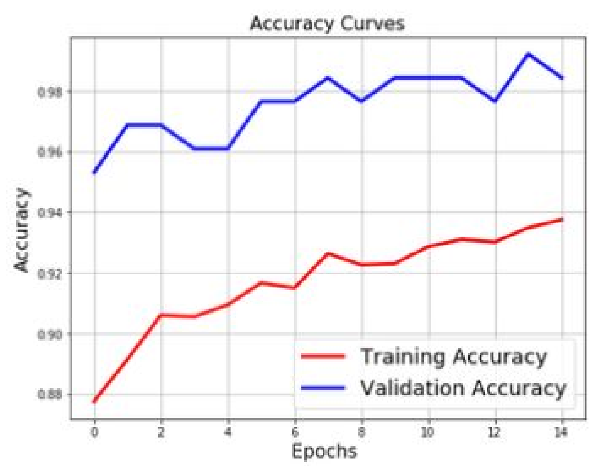
The main hurdles that machine learning algorithms face in being accepted formally for clinical predictive analyses is the issue of interpretability and accuracy. Here, we attempt to create a tool that diagnoses common treatable retinal diseases using deep learning framework while keeping the hurdles in mind.

We use conventional approaches by the ImageNet database to train the neural networks using a method of training which is known as transfer learning. We apply this algorithm to a dataset comprised of optical coherence tomography images. The results are found to be comparable to diagnosis of age-related or diabetic macular regeneration by human experts.

The graph shows the training loss and validation loss for 14 epochs where they are closing in, if we increase the number of epochs we can still decrease the validation loss.



The model is performing well on the validation set and training set where the accuracy is close, we can conclude the model is not overfitting.



This model has been tested and yielded 97.84% accuracy.

Preprocessing the data and image augmentation were challenging but running the model multiple times which took long hours to complete was one of the major challenges as the data set was large.

V. RESULTS

Early detection of diseases is a very novel use of deep learning and should be improved and integrated into healthcare as much as possible. With growing data and number of patients due to an increase in unhealthy lifestyles it can help in hospital management in many ways. The model we have created is built on this principle. It helps doctors to quickly and preemptively predict diseases and start treatment early on. It has a user friendly GUI website that anyone can use. We have dealt with four major diseases namely Brain Tumour, Malaria and Retinal OCT.
This model has achieved test accuracy of about 97 percent for Malaria prediction. We have achieved 88.7 percent accuracy while predicting presence of brain tumors. While we have achieved a benchmark accuracy of 97.4 percent for Retinal OCT scans.Due to efficient GPU usage of convolutional methods the models give fast results making the segmentation methods for various uses practical.

The main focus of this model has been on increasing the prediction accuracy and reducing the chances of false negatives as well as false positives as we can't take chances in the area of healthcare. We have been successful in doing this. This project has a lot of future scope. This model can be easily extended to include any number of diseases. We can develop a fully fledged system with a backend central database to store our results and patient data. This can be used in the healthcare sector. With the smart cities market booming healthcare will be one of the main spending areas and this model can be improved and used for this purpose.

VI. CONCLUSION

Our efforts have been to detect chronic diseases before they become severe and merit a hospitalization. We have combined all the three diseases in a Web GUI interface which can run on any local computer.Further this can be hosted online using various cloud platforms to make it publically accessible.

There could have been further improvement in the image augmentation part. Also there could have been different better pretrained models could be implemented like ResNet50 which could provide much better accuracy.

VII. REFERENCES

[1] Tal Baumel, Jumana Nassour-Kassis.“ Multi-label Clas-sification of Patient Nodes: A Case Study on ICD code assignment”

[2] Edward Choi, Mohammad Taha Bahadori.“Doctor AI:Predicting Clinical Events via Recurrent Neural Networks”

[3] Tianyong Hao, Hongfang Liu.“Valx: A System for Extracting and Structuring Numeric Lab Test Comparison Statements from Tex”

[4] Sepp Hochreiter and Jurgen¨ Schmidhuber. Long short-term memory. Neural computation, 9(8): 1735–1780, 1997.

[5] Yoon Kim.“Convolutional Neural Networks for Sentence Classification”

[6] Zachary C. Lipton, David C. Kale. “Learning to diagnose with LSTM Recurrent Neural Networks”

[7] Theodora S. Brisimi, Tingting Xu, Taiyao Wang, ”Predicting chronic disease hospitalizations from Electronic HealthRecords: An Interpretable Classification approach”

[8] Edward Choi, Mohammad Taha Bahadori. “GRAM:Graph-based Atten-tion Model for Healthcare Representation Learning”

[9] Jingshu Liu, Zachariah Zhang. “Deep EHR: Chronic Dis-ease Prediction Using Medical Notes”

[10] Junyoung Chung,Caglar Gulcehre. “Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling”

[11] Yach D, Hawkes C, Gould CL, Hofman KJ. The global burden of chronic diseases: overcoming impediments to prevention and control. Jama. 291(21):2616–2622.2004; [PubMed: 15173153]

[12] Hannan TJ. Detecting adverse drug reactions to improve patient outcomes. International Journal of Medical Informatics. 55(1):61–64.1999; [PubMed: 10471241]

[13] Madalina Fiterau, Suvrat Bhooshan, Jason Fries, Charles Bourn-honesque, Jennifer Hicks, Eni Halilaj, Christopher Re,´ and Scott Delp. Shortfuse: Biomedical time series representations in the presence of structured information. arXiv preprint arXiv:1705.04790, 2017.

[14] Truyen Tran, Wei Luo, Dinh Phung, Jonathan Morris, Kristen Rickard, and Svetha Venkatesh. Preterm birth prediction: Deriving stable and interpretable rules from high dimensional data.

[15] David Sontag and Narges Razavian. Temporal convolutional neural networks for diagnosis from lab tests.

[16] Zhengping Che, Kyunghyun Cho, Sanjay Purushotham, David Sontag, and Yan Liu. 2016. Recurrent Neural Networks for Multivariate Time Series with Missing Values. arXiv:1606.01865 (2016).

[17] Edward Choi, Elizabeth Searles, Mohammad Taha Bahadori, Catherine Coffey, James Bost, Michael Thompson, Jimeng Sun, and Jimeng Sun Javier T Sojo. 2016. Multi-layer Representation Learning for Medical Concepts. In SIGKD

[18] Harini Suresh, Nathan Hunt, Alistair Edward William Johnson, Leo Anthony Celi, Peter Szolovits, and Marzyeh Ghassemi. Clinical intervention prediction and understanding using deep networks. CoRR, abs/1705.08498, 2017.

[19] Ledell Wu, Adam Fisch, Sumit Chopra, Keith Adams, Antoine Bordes, and Jason Weston. Starspace: Embed all the things! arXiv preprint arXiv:1709.03856, 2017.

[20] Alex Graves, Abdel-rahman Mohamed, and Geoffrey Hinton. Speech recognition with deep recurrent neural networks. In Acoustics, speech and signal processing (icassp), 2013 ieee international conference on, pages 6645–6649. IEEE, 201