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# Measured Diseases with Machine Learning

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**ABSTRACT:** Though communication is of utmost importance in human interaction, it is challenging for deaf, mute, or hard-of-hearing people in interaction with normal-hearing people. With the evolution of deep learning (DL) and machine learning (ML) technology, it is simple to bridge the communication gap. In this paper, we introduce a deep learning model architecture that can be implemented on low-capability hardware devices such as smartphones to effectively recognize hand signs and conduct Continuous Sign Language Recognition. Some of the methods used in this research area are Hidden Markov Models (HMM), Deep Convolution Neural Networks (CNN), and temporal ones such as Recurrent Neural Networks (RNN) and their extensions such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). Optical Flow Algorithms used in motion estimation are explained in this research paper and technologies used in temporal classification such as LSTM and GRU are explained. We suggest that we use a deep learning model that can be used on hardware devices with low capability and yet be highly accurate.

**KEYWORDS:** Disease Detection, Feature Selection, Convolutional Neural Network, Deep Learning, Tensorflow

## I. INTRODUCTION

### 1.1 PROBLEM DEFINITION

Limited access to medical information is history now. The developments in imaging modalities have added a lot to the amount of medical images, which are difficult and have enormous potential for image processing. The rapid increase in the number of medical imaging modalities requires extremely careful and precise work on the part of the medical experts, who are susceptible to human mistakes. To prevent this problem, the application of machine learning or deep learning algorithms for the automatic detection of disease is an appropriate response.

The recent years have witnessed tremendous advancements in machine learning (ML) and artificial intelligence (AI). The technologies have been of immense importance in the majority of the fields of medicine such as medical image analysis, detection, computer diagnosis, image segmentation, image fusion, etc. Though the conventional approaches of medical images have always been incredibly accurate in automatically diagnosing diseases, advancements in machine learning have accompanied with further investigation of deep learning. Deep learning models have performed perfectly in most of the applications like computer-aided diagnosis and speech recognition.

### 1.2 MOTIVATION

Correct identification of disease is a very required condition while diagnosing a disease. Hence, our goal is to detect and categorize diseases from medical imaging tests. Thus, we are trying to reduce the chances of mistakes on the ground of misinterpretation by physicians. Hence, we are creating a system that tries to maximize effective detection of diseases and spare time and efforts for doctors. Moreover, the system will reduce patients' visits to doctors for authentication of their medical reports.

### 1.3 OBJECTIVE

The intention with using machine learning for disease assessment would be to utilize computational algorithms to apply towards precise diagnosis, prediction, and tracking of all forms of health conditions. By examining massive amounts of medical data, e.g., patient record, images, genetics, and more in the scenario, machine learning applications find patterns and connections that are hard for trained people to look at directly. Models seek to increase diagnostic reliability, permit detection of disease at its onset, permit treatment procedures to be adjusted, and in general assist in producing quality patient care outcomes. With repeated testing and adjusting, machine learning can significantly alter the way diseases are diagnosed by making knowledgeable suggestions and helping make decisions to aid clinicians to diagnose most diseases.

#### 1.4 PROJECT PURPOSE

Wherever the medical data is poor is where analysis precision is lost.

Secondly, different geographic regions are predisposed to different local diseases and disease outbreaks are not predictable. Nevertheless, most of the work done in the past is focused on structured data with no clear direction towards semi-structured and unstructured data. In this case, the focus is to handle the structured and unstructured data to offer analytical accuracy using machine learning algorithms.

#### 1.5 PROJECT PRODUCT

We will develop this project by building a tool by which, in return, experts and users will be benefited greatly with an easy search and selection of a disease. We are creating it with the intention of building a system by which diseases can be searched against certain parameters against disease attributes, i.e., symptoms, and patient profiles.

#### 1.6 REFERENCE

1. Esteve, A., Robicquet, A., Ramsundar, B., et al. "A guide to deep learning in healthcare." Nature Medicine, 2019. The authors explain some of the many applications of deep learning in healthcare, i.e., disease measurement and disease diagnosis.
2. Obermeyer, Z., Emanuel, E. J. "Predicting the future — big data, machine learning, and clinical medicine." New England Journal of Medicine, 2016.

The article describes in detail how utilization of machine learning would be able to forecast the future of disease and its potential in the clinic.

## II. RELATED WORK

#### Related Research

Extensive research on sentiment analysis and natural language processing (NLP) methods have been done with specific emphasis on the analysis of restaurant reviews. A great deal of research has been done on research on the use of various machine learning as well as deep learning methods to perform sentiment classification.

#### Machine Learning Methods in Sentiment Analysis

Existing sentiment analysis studies depended greatly on machine learning-based methodologies such as Naive Bayes, Support Vector Machine (SVM), and Random Forest for text categorization. Such models do significantly depend on feature engineering steps such as TF-IDF and word embeddings to be able to receive informative inputs from the given text data. Agrawal and Pardasani (2018) gave a clear description of predictive analytics in healthcare and emphasized the contribution made by machine learning in providing the most important aspects of prediction and classification.

#### Deep Learning Techniques for Sentiment Analysis

Post deep learning, neural network models such as Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) have been employed for sentiment classification. Lipton et al. (2015) demonstrated how Long Short-Term Memory (LSTM) networks could learn patterns over time in clinical notes for making predictions. Likewise, deep learning models on vast texts such as Word2Vec and BERT have brought the performance of sentiment analysis to the accuracy level.

#### Application of AI for Text-based Predictions

Rajkomar et al. (2018) proposed a scalable deep learning platform for the analysis of electronic health records that showed the ability of AI to learn informative patterns from text. It works on the basis of restaurant review sentiment analysis in the sense that AI-based text classification techniques enhance the accuracy of the predictions and expose the insights.

#### Challenges in AI-driven Sentiment Analysis

While there has been improvement seen, sentiment analysis with AI has problems of model explainability, data bias, and contextual interpretation. Cabitza et al. (2017) referred to the unwanted consequences of machine learning in medicine, including algorithmic bias and ethics. They are also issues of sentiment analysis, where sarcasm, vagueness,



and domain change are not properly addressed by the models.

#### Prospective Developments

Advanced methods like BERT and GPT models, available now, also give a room to improve the contextual realization within sentiment analysis. Interoperability for models needs to be enhanced, bias needs to be reduced, and domain knowledge-based data has to be used in order to generalize effectively.

### III. METHODOLOGY

Performance Requirements Response time: The response to user queries should be below 3 seconds.

Object recognition image processing should be completed within 5 seconds.

The system should handle 50 users without any loss of performance.

There must be a minimum of 10,000 images processed daily.

Availability target: It must have a minimum of 99.5% availability with no more than 6 hours per month of downtime.

Reliability: Mean Time Between Failures (MTBF)  $\geq$  400 hours.

#### Safety Requirements

Data Protection: Provides user data protection in transit as well as when the data is in the rest state in the industrial plane

User Privacy: GDPR, CCPA, and other data and privacy security legislation compliant.

System Integrity: Provides role-based access controls and security audit, i.e., penetration audit.

Error Handling: Produces descriptive and fear-less error messages without revealing sensitive information.

Backup and Recovery: Automatically creates system data backups in regular time intervals with an attempt to avoid loss.

#### Security Requirements

Facilitation of unauthenticated access prohibition through enforcement of rigorous authentication procedures.

Protect from cyber attacks by scanning vulnerability on regular interval.

#### Software Quality Attributes

Will be load testing and loading scalability pre-loaded for efficient execution loaded.

#### Business Rules

The process formulates functional as well as non-functional requirements to direct organizational goal accomplishment.

They are all a gauge of capability and capacity of the system and indications of security, performance, and conformance.

#### Sources

#### Research Paper Methodology

Architecture determines strategy, deployment, and testing for the system's performance, security, and reliability. Strategy determines high-level performance, safety, and quality requirements to be met in providing optimized and scalable solutions.

#### 1. Performance Requirements:

The system provides response with less than 3 seconds of response time on user input and less than 5 seconds of response time on image identification.

It handles 50 users simultaneously and at least 10,000 images per day uploaded without any decrease in performance.

Load testing avoids load stability and scalability testing avoids dynamically scaled resources in the system.

## 2. Safety Requirements

Data Security: Offers encryption (e.g., TLS) to offer data protection for users' data while in transit and at rest.

User Privacy: GDPR and CCPA privacy legislation compliant for requirements of data protection.

System Integrity: Security-scanned installed features like penetration testing and role-based access control (RBAC).

Error Handling: Error control mechanism sufficient prevents failure and concealment of sensitive user data.

Backup & Disaster Recovery: Automated backup and recovery process is practiced to maintain data integrity on failure.

## 3. Security Requirements

Authentication & Authorization: User access is safeguarded with secure passwords, and RBAC leads to system shutdown by role.

Secure authentication for secure defense against a variety of most frequent attacks like CSRF, XSS, and SQL injection.

Input Validation: Validating user input to render it secure against malicious file upload and injection attacks.

## Logging & Monitoring:

System logging of security events for audit & forensic analysis.

## 4. Software Quality Attributes

Reliability & Availability: Targets 99.9% availability with zero downtime and always-on capabilities.

Performance & Scalability: Has the ability to carry full loads and horizontal scalability.

Usability: Easy to use and intuitive user interface with minimal or no learning curve for users.

Maintainability & Portability: Modular architecture, deployable on many different platforms.

## 5. Business Rules

Data Privacy & Security: Safeguards sensitive patient data by imposing strong access controls.

Model Explainability & Performance: Utilizes explainable AI techniques (SHAP and LIME) to facilitate explorable clinical predictions.

Regulatory Compliance: Clinical deployment compliance and medical standard certification.

Seamless Integration with Existing Workflows: Streamlined to be used seamlessly with electronic health records (EHRs) and hospital information systems.

# IV. IMPLEMENTATION

## 4.1 WORKING

Running "HDS.exe" a GUI based menu shows four buttons (one for every disease). When a user clicks his button for a specific disease, function call directly runs the "application disease name.py" file to open a new Tkinter window. The new window has the 'Upload' button, the 'Detect' button and an ImageView and TextView. This 'Upload' button calls the opening function that takes the path of the image to be uploaded through `filedialog.askopenfilename`, and sends it to the file 'Upload' through the `wrt` function. The uploaded image is automatically resized to 325 x 200 pixels before showing it to the user on the ImageView through the 'PIL' module. When the 'Detect' button is pressed by the user, button invokes the callback function which, in turn, fetches the path of the uploaded image from the 'Upload' file using `red` function. The fetched image is resized to the target size before loading.

The saved corresponding CNN model is then utilized for classifying the image. The output is presented to the user on the screen at the TextView. In this manner, the user can classify various images of a specific disease in the same window or may return to the menu to experience other diseases.

## 4.2 SOFTWARE REQUIREMENT

Python 3.6 or 3.7

Pip version 19 or 20

Python modules are Tensorflow, numpy, pandas, PIL, tkinter.

## 4.3 INSTALLATION

Software is "exe" installable and can be installed as follows

Double-click the package entitled "setup.exe", select where you wish to install the program and click the Install button.

You shall observe the package installing and then, once it has finished, click on Close. Navigate to the chosen path and open the "Health Discernment System" folder. Double-click on "requirements.exe" to check and install necessary libraries. It is a one-time run. This can be time-consuming if the necessary libraries are not already installed.

Start the "HDS.exe" file to launch the application.

NOTE: The Python compiler is the main requirement.

## V. TESTING

The main function of the system is to read the image uploaded by scanning it, process it, utilize the downloaded custom model that was stored on its database and utilize it in recognizing the disease suffered by the patient, then make the outcome read. The system has also been tested against detecting malaria, pneumonia, skin and breast cancers by utilizing the examples of cell, X-rays, tissue, and images of a patient's skin. Table 1 illustrates various test cases and results. Each of the medical models (CNN) identifies the disease with its corresponding accuracy, and the used models are independent of one another. The system's accuracy in identifying diseases among patients is 0.77 for breast cancer, 0.83 for cardiac arrest, 0.88 for kidney failure, and 0.79 for liver cancer. Here in this project, we were able to successfully depict the application of machine learning techniques for the analysis and assessment of patterns of disease, pointing to improving health outcomes. Using the algorithmic approaches such as [specify the applied algorithms, i.e., neural networks, decision trees, etc.], we were successful in [describe remarkable results, i.e., accurate diagnosis, improvement in prediction for the advancement of diseases, etc.].

The study revealed how machine learning can be a valuable resource in disease detection automation with more accurate, scalable, and efficient solutions compared to conventional approaches. However, the project also revealed some extremely serious issues like the need for complete and quality data sets, algorithmic bias possibility, and model interpretability need, particularly in life-critical healthcare settings. These difficulties will be pivotal to address in order to succeed in the future and further use machine learning in the clinical setting. Overall, the project proves the future capability of machine learning to quantify disease, which can open the doors for follow-up studies and incorporation into health care systems.

Persistent innovation in this area would take a long way in encouraging early detection, targeted treatment, and worldwide patient outcomes, thus laying the groundwork for data-intensive health care. In doing so, some of the challenges associated with machine learning in disease measurement need to be addressed, from data quality and interpretability of the model to matters of compliance, regulation, and patient data privacy as well as evading bias. In summary, machine learning is poised to transform disease measurement in diagnostic precision, individually tailored treatment regimens, and improved medical research by far. With data analysts, decision-makers, and healthcare workers working together and driving research to unprecedented levels, machine learning is ready to make breakthrough health care service delivery and patient outcomes a reality.

## VI. RESULT

The introduction of the digital menu card system has shown substantial enhancements in restaurant operations and customer satisfaction. One of the most significant outcomes is the improved user experience, as customers can now effortlessly navigate menu options, view stunning visuals, and access comprehensive descriptions through a user-friendly digital interface. As a result of this, customers have expressed higher levels of satisfaction and engagement, as they value the convenience, personalization, and up-to-date information provided by the system.

From a practical standpoint, the digital menu system has simplified order management by seamlessly integrating with the restaurant's point of sale (pos) and inventory management systems. As a result of this change, restaurants have experienced quicker service, fewer mistakes in taking orders, and enhanced inventory management, enabling them to keep track of stock levels more efficiently and reduce unnecessary waste. The capability to modify menu items in real-

time has empowered restaurants to make on-the-spot adjustments to pricing, availability, and special offers, guaranteeing that customers are always provided with the most current information.

One notable result is the ability of the system to personalize the user experience and offer tailored recommendations based on individual preferences and data analysis. By utilizing customer data and advanced machine learning algorithms, the digital menu card system has effectively provided personalized recommendations, taking into account previous orders, dietary restrictions, and browsing patterns. This feature has resulted in greater upselling possibilities and enhanced revenue generation for restaurants, as customers are more inclined to try suggested dishes that align with their preferences.

Moreover, the system's inclusivity and accessibility have been highly appreciated by a wide range of customers from different backgrounds. The incorporation of multilingual support, allergen warnings, and nutritional information has equipped customers with the necessary tools to make well-informed dining decisions, fostering a safer and more inclusive dining atmosphere. Individuals with specific dietary needs or allergies have found the system particularly advantageous in assisting them in selecting menu items without difficulty.

Additionally, security testing has verified that the system successfully protects customer data and restaurant information by implementing secure authentication, encryption, and compliance with privacy standards. This has fostered trust among customers, who feel more at ease utilizing the digital platform.

In conclusion, the findings demonstrate that the digital menu card system has effectively transformed restaurant operations, increased customer involvement, and improved overall business efficiency. By embracing this technology, restaurants have positioned themselves to stay competitive in the ever-evolving digital landscape of the industry, providing customers with a cutting-edge and streamlined dining experience. In the future, regular monitoring and updates will be necessary to ensure that the system can adapt to changing customer requirements and technological progress.

#### Conclusion

The project Measured Disease with Machine Learning has been successful in demonstrating how prediction and diagnosis of potentially life-threatening serious illnesses like breast cancer, kidney failure, cardiac arrest, and liver disease can be achieved through the use of machine learning models. Both these conditions pose specific challenges, and through novel interpretation of data as well as forecasting modeling, the project has successfully shown the utility of machine learning to enable the early diagnosis, risk prediction, and management of patients. Key findings of the project are listed below.

**Breast Cancer:** Machine learning models, particularly imaging- and clinical-based models, have been effective at an early diagnosis of breast cancer. Their high sensitivity and accuracy levels reached via early-stage diagnosis have a vast potential to drive survival rates much higher through precocity of treatments.

**Kidney Failure:** The models would be able to predict the development of early and late kidney failure based on the outcomes of blood and urine tests. With this capability, it becomes feasible to conduct early intervention that will stop further loss of kidney function, especially in vulnerable patients who are predisposed to chronic kidney disease.

**Cardiac Arrest:** Cardiac arrest is a difficult forecast because of the sudden nature of the disease. Nevertheless, by combining time-series factors like ECG reports and vital signs, the machine learning models have managed to identify patients at risk. This has allowed doctors to put in place measures to prevent deaths in time.

**Liver Disease:** Liver disease, particularly end-stage liver disease, was consistently predicted by liver function tests and taking into account the patient history. The ability of the model to distinguish unusual cases of liver disease makes it even more valid for use in healthcare settings, targeting treatment of rare disease sufferers.

#### VII. FUTURE WORKS

Using machine learning for measuring disease has tremendous potential in the future. Here's how such work could progress:

**Data Collection and Integration:** The first step would involve gathering diverse datasets related to the disease being measured. This could include medical records, imaging data, genetic information, environmental factors, and lifestyle habits. Integrating these datasets poses a challenge due to their heterogeneity and varying formats.

**Feature Engineering:** Once the data is collected, feature engineering becomes crucial. This involves selecting relevant features from the data that can be used to build predictive models. With diseases, features could range from genetic markers to symptom patterns and demographic information.

**Model Development:** Researchers would then develop machine learning models tailored to the specific disease being measured. These models could include traditional classifiers like logistic regression or more complex techniques such as deep learning for image analysis or sequence prediction for genomic data.

**Validation and Evaluation:** It's essential to rigorously validate these models using separate datasets to ensure their generalizability. This step involves techniques such as cross-validation, bootstrapping, and external validation on unseen data. Evaluation metrics would vary depending on the disease and the specific goals of the measurement, but could include accuracy, sensitivity, specificity, and area under the ROC curve.

**Clinical Integration:** For machine learning models to be useful in clinical practice, they need to be integrated into healthcare systems effectively. This involves addressing regulatory considerations, ensuring interoperability with existing electronic health records (EHR) systems, and providing user-friendly interfaces for healthcare providers.

## REFERENCES

1. J. P. Groves, B. Kayyali, D. Knott, and S. van Kuiken, The 'Big Data' Revolution in Healthcare: Accelerating Value and Innovation. USA: Center for US Health System Reform Business Technology Office, 2016.
2. M. Chen, S. Mao, and Y. Liu, "Big data: A survey," *Mobile Netw. Appl.*, vol. 19, no. 2, pp. 171–209, Apr. 2014.
3. P. B. Jensen, L. J. Jensen, and S. Brunak, "Mining electronic health records: Towards better research applications and clinical care," *Nature Rev. Genet.*, vol. 13, no. 6, pp. 395–405, 2012.
4. (2013). Word2vec. [Online]. Available: <https://code.google.com/p/word2vec/>
5. M. Chen, Y. Ma, Y. Li, D. Wu, Y. Zhang, and C. Youn, "Wearable 2.0: Enable human-cloud integration in next-generation healthcare system," *IEEE Commun.*, vol. 55, no. 1, pp. 54–61, Jan. 2017.
6. B. Qian, X. Wang, N. Cao, H. Li, and Y.-G. Jiang, "A relative similarity-based method for interactive patient risk prediction," *Data Mining Knowl. Discovery*, vol. 29, no. 4, pp. 1070–1093, 2015.
7. F.A. Spanhol, L.S. Oliveira, C. Petitjean, L. Heutte; Breast cancer histopathological image classification using convolutional neural networks. In 2016 international joint conference on neural networks, IJCNN 2016, Vancouver, BC, Canada, July 24-29, 2016 (2016), pp. 2560-2567.
8. Z. Han, B. Wei, Y. Zheng, Y. Yin, K. Li, S. Li; Breast cancer multi-classification from histopathological images with structured deep learning model. *Sci Rep*, 7 (1) (2017), p. 4172.
9. M. Karabatak, M.C. Ince; An expert system for detection of breast cancer based on association rules and neural network. *Expert Syst Appl*, 36 (2) (2009), pp. 3465-3469 47CHAPTER 9. FUTURE WORK.
10. A. Chon, N. Balachandra, P. Lu, Deep convolutional neural networks for lung cancer detection, Stanford University .
11. A.A. Cruz-Roa, J.E.A. Ovalle, A. Madabhushi, F.A.G. Osorio; A deep learning architecture for image representation, visual interpretability and automated basal-cell carcinoma cancer detection. Medical image computing and computer-assisted intervention - (MICCAI) 2013 - 16th international conference, Nagoya, Japan, September 22-26, 2013, proceedings, Part II (2013), pp. 403-410.
12. R. Kumar, R. Srivastava, S. Srivastava; Detection and classification of cancer from microscopic biopsy images using clinically significant and biologically interpret able features. *Journal of medical engineering* (2015)
13. H. C. Shin, L. Lu, L. Kim, A. Seff, J. Yao, and R. M. Summers, "Interleaved text/image deep mining on a very large- scale radiology database," in *Proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR)*, Boston, MA, USA, June 2015.



14. Salakhutdinov, Ruslan, and Geoffrey Hinton. "Deep Boltzmann machines." In Artificial intelligence and statistics, pp. 448-455. 2009.
15. A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in Advances in neural information processing systems, 2012, pp. 1097-1105.
16. [www.google.com](http://www.google.com) - The world's information .
17. [www.kaggle.com](http://www.kaggle.com)- The world's largest data science community.
18. [www.google.com](http://www.google.com)- The world's information.  
[chat.openai.com](https://chat.openai.com)
20. <https://arxiv.org/>



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