Machine Learning and Deep Learning Methods for Building Intelligent Systems in Medicine and Drug Discovery: A Comprehensive Survey

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ABSTRACT

With the advancements in computer technology, there is a rapid development of intelligent systems to understand the complex relationships in data to make predictions and classifications. Artificial Intelligence based framework is rapidly revolutionizing the healthcare industry. These intelligent systems are built with machine learning and deep learning based robust models for early diagnosis of diseases and demonstrates a promising supplementary diagnostic method for frontline clinical doctors and surgeons. Machine Learning and Deep Learning based systems can streamline and simplify the steps involved in diagnosis of diseases from clinical and image-based data, thus providing significant clinician support and workflow optimization. They mimic human cognition and are even capable of diagnosing diseases that cannot be diagnosed with human intelligence. This paper focuses on the survey of machine learning and deep learning applications in across 16 medical specialties, namely Dental medicine, Haematology, Surgery, Cardiology, Pulmonology, Orthopedics, Radiology, Oncology, General medicine, Psychiatry, Endocrinology, Neurology, Dermatology, Hepatology, Nephrology, Ophthalmology, and Drug discovery. In this paper along with the survey, we discuss the advancements of medical practices with these systems and also the impact of these systems on medical professionals.

1. Background

Machine learning and deep learning are the subsets of artificial intelligence as shown in figure [1] that have witnessed rapid growth over the years. These techniques have proved to be effective in diagnosing diseases across various specialties in medicine.

1.1. Machine learning

Machine Learning techniques are statistical models that are used to make predictions and classifications on the given data. The machine learning models are categorized into two types based on the type of learning techniques namely supervised and unsupervised [Angra and Ahuja (2017)]. In supervised learning [Singh et al. (2016)], the machine learning model is trained with a set of input data (or features) that are associated with known output. Once the training of the machine learning model is successful, it is capable of making predictions on the new data. The predictions made by the supervised-learning algorithms can be continuous or discrete. Some of the examples of supervised learning algorithms are random forests, decision trees, logistic regression, K-nearest neighbors, and support vector machines [Muhammedev et al. (2015), Telson et al. (2019), Obulesu et al. (2018), Narayanan et al. (2017)]. These techniques are used for diagnosing diseases like diabetes, thyroid, diabetic retinopathy,
1.2. Deep learning

Deep learning is a subset of the broad family of machine learning. Deep learning models are successful in solving problems related to image classification and natural language processing. These deep learning algorithms (Lauzon 2012) are based on neural networks, these networks have multiple layers for extracting high-level features and for eliminating problematic features, so the performance of deep learning algorithms is higher than machine learning algorithms. Some of the widely used deep learning architectures (Shrestha and Mahmood 2019) are Convolutional Neural Networks (CNN), Recurrent neural networks (RNN), and generative adversarial neural networks (GAN). Convolutional neural networks (Albawi et al. 2017) are mostly used for solving computer vision and image classification tasks. CNN’s reduce the number of parameters compared to fully connected neural networks. Convolutional neural networks are used for organ segmentation, identification of tumors, classification of various cancers from radiology images. The basic structure of CNN for classification and segmentation are shown in Figure 2.

RNN’s are used for solving audio recognition and natural language processing problems. RNN’s (Khalaf et al. 2017) can be used for sequential data analysis as they show temporal dynamic behavior. This property of RNN can be used for aiding fractional radiotherapy. GAN’s are generative models (Yang et al. 2017), when given a training dataset these models are capable of generating new data that have the same statistics as the training data. GAN’s learn with an adversarial competition between its discriminator and generator. GAN’s are used mainly for medical image synthesis and for image augmentation of the training data to avoid problems like overfitting and data scarcity. The basic structures of RNN and GAN are shown in Figure 3.

In this paper, we present a survey of various machine learning (ML) and deep learning (DL) models that can be used for building intelligent systems for the diagnosis of various diseases in 16 medical specialties of healthcare. Along with the 16 medical specialties we present the survey of ML and DL models in drug discovery. The 16 medical specialties that are considered for this work are Dental medicine, Haematology, Surgery, Cardiology, Pulmonology, Orthopedics, Radiology, Oncology, General medicine, Psychiatry, Endocrinology, Neurology, Dermatology, Hepatology, Nephrology, and Ophthalmology. Along with the survey, we discuss the advancements in medicine with machine learning and deep learning-based diagnostic systems and also the impact of these systems on medical professionals. The rest of the paper is organised as follows, Section 2 describes the survey methodology, Section 3 describes the literature review, Section 4 discusses the impact of these methods, Section 5 concludes the work and finally Section 6 presents the suggestions for future work.

2. Survey methodology

The articles that were surveyed in this paper are presented and published in high-quality conferences and journals of IEEE, Elsevier, ACM, and Springer. The terms that are used for searching these articles include machine learning, deep learning, dental medicine, hematology, surgery, cardiology, pulmonology, orthopedics, radiology, oncology, general medicine, psychiatry, endocrinology, neurology, dermatology, hepatology, nephrology, ophthalmology, and drug discovery. The articles that are considered for this survey are directly related to the topic of machine learning and deep learning applications in medicine and drug discovery. For this work, both empirical and review articles related to the above topics were considered.

3. Literature review

3.1. Dental medicine

Table 1 shows some of the popular approaches used by the researchers to diagnose dental diseases. (Prajapati et al. 2017) used machine learning approaches to classify three different diseases, namely dental caries, periodical infection, and periodontitis. The authors considered a dataset of 251 radio videography (RVG) x-ray images for classification, out of which 80 images are of dental caries, 110 images are of periodical infection, and 61 images of periodontitis. Three models were built they are Convolutional neural network (CNN), transfer learning of CNN with VGG16 as a feature extractor, and CNN transfer learning model with fine-tuning. A fuzzy rule-based model is designed by (Tuan et al. 2017) to diagnose dental diseases. In this model, different methods are used for feature extraction; they are entropy, edge-value, intensity, and local binary patterns, gradient feature, red-green-blue, and patch level feature. These extracted features are used to make a database. For this work, Fuzzy c-means clustering and Mamdani’s fuzzy interface methods were used. Machine learning algorithms are
used by Vera et al. (2010) for optimizing the dental milling process. In this paper, two models of feedforward networks were designed with Bayesian regularisation and early stopping technique. The artificial neural network structure of a feedforward network built using Bayesian regularisation has two layers, the first layer with 5 hyperbolic target units and the second layer with 30 hidden hyperbolic target units and one output unit. The structure of the second feedforward network built using the early stopping technique has the same layers as the first model, but these two networks are estimated separately using the Levenberg-Marquardt method and quasi-Newton methods. The performance of these models is shown Table 1.

### 3.2. Haematology

The diagnosis of blood-related diseases is very complicated and time-consuming. Machine learning techniques are used by Haematologists to diagnose diseases accurately in less time. Ongun et al. (2001a) used machine learning classification techniques to build a model that automates the differential blood counting system. The segmentation of images is done using contour models, namely snakes and balloons. Texture and shape-based features are considered for classification. Four machine learning classifiers are used for classification; they are K-Nearest Neighbour, Linear vector quantization, Multilayer perceptron, and support vector machine. The accuracies of the classifiers are shown in table ?? . The application of machine learning for the segmentation and tracking of thrombus is proposed by Peter et al. (2012a). Adaboost and Decision tree models are used for segmentation, and the K-nearest neighbor algorithm is used for tracking. These classification algorithms are evaluated based on the Dice coefficient, and positive predictive value and tracking method are evaluated based on the Dice coefficient. The classification of sickle cell disease using machine learning is proposed by Khalaf et al. (2016a). For this work, the performances of various machine learning algorithms are analyzed, as mentioned in table 2, from which Levenberg-Marquardt and random forest algorithms produced excellent results.

### 3.3. Surgery

Machine learning techniques are used as a decision support system for post-operative planning and as a navigation system for many of the critical surgeries. For understanding the functioning of knee implants after the Surgery, Kobashi et al. (2016) used machine learning techniques for building a statistical model. The mapping function of the proposed model in this
### Table 1. ML and DL methods in Dental medicine.

| Author                | Method                        | Diagnosis/Application                                      | Metrics          | Findings  |
|-----------------------|-------------------------------|-----------------------------------------------------------|------------------|-----------|
| Prajapati et al. (2017) | CNN                           | Dental caries, periodical infection, and periodontitis     | Accuracy         | 0.7307    |
|                       | Transfer learning             |                                                           |                  | 0.8846    |
|                       | Transfer learning with fine tuning |                                                   |                  | 0.8846    |
| Tuan et al. (2017)    | Fuzzy Interface System        | Abnormalities in dental x-ray                            | Mean Square Error| 0.2445    |
|                       |                               |                                                           | Mean Absolute Error| 0.1264    |
|                       |                               |                                                           | Accuracy         | 90.29%    |
| Vera et al. (2010)    | Feedforward network with early stopping | Optimization of dental mining process                    | Normalized Mean error | 89.95%    |
|                       | Feedforward network with Bayesian regularisation |                       | Normalized Mean error | 87.98%    |

### Table 2. ML and DL methods in Haematology.

| Author                | Method                        | Diagnosis/Application                                      | Metrics          | Findings  |
|-----------------------|-------------------------------|-----------------------------------------------------------|------------------|-----------|
| Ongun et al. (2001a)  | K-Nearest Neighbour          | Automation of differential blood counting system           | Accuracy         | 81%       |
|                       | Linear vector Quantization    |                                                           | Accuracy         | 83%       |
|                       | Multi Layer Perceptron       |                                                           | Accuracy         | 90%       |
|                       | Support Vector Machine       |                                                           | Accuracy         | 91%       |
| Peter et al. (2012a)  | Decision Tree                | Thrombus                                                  | Dice coefficient | 0.89 ±0.02|
|                       | Ada Boost                     |                                                           | Positive predicted value | 0.94 ±0.04|
|                       | Tracking                     |                                                           | Dice Coefficient | 0.87 ±0.02|
|                       |                               |                                                           | Positive predicted value | 0.90 ±0.05|
|                       |                               |                                                           | Positive predicted value | 0.94 ±0.05|
| Khalaf et al. (2016a) | Random Oracle model          | Sickle cell disease                                        | Accuracy         | 53.9%     |
|                       | Levenberg-Marquardt learning algorithm |                                       | Area Under ROC Curve | 0.524     |
|                       | Trainable decision tree Classifier |                                              | Accuracy         | 99.2%     |
|                       | Random Forest, Decision Tree Ensemble Classifier |                           | Area Under ROC Curve | 0.991     |
|                       | Levenberg-Marquardt learning algorithm and Random Forest, combined using Levenberg neural network | | Accuracy         | 92.1%     |
|                       | Area Under ROC Curve          |                                                           | 0.95              |
|                       | Area Under ROC Curve          |                                                           | 0.915             |
|                       | Levenberg-Marquardt learning algorithm and Random Forest, combined using Fischer discriminate analysis | | Accuracy         | 99.2%     |
|                       | Area Under ROC Curve          |                                                           | 0.988             |
|                       | Levenberg-Marquardt learning network and Random Forest, combined using Fischer discriminate analysis | | Accuracy         | 98.9%     |
|                       | Area Under ROC Curve          |                                                           | 0.995             |
|                       | Functional link neural network |                                                           | Accuracy         | 96.2%     |
|                       | Linear Combiner Network       |                                                           | Area Under ROC Curve | 0.972     |
|                       |                               |                                                           | Accuracy         | 84%       |
|                       |                               |                                                           | Area Under ROC Curve | 0.849     |
The paper is built using the pre and post-operative features, which are extracted using Principle component analysis from the clinical database. The evaluation results are shown in Table 3. Minimal invasive surgeries are being performed by surgeons to avoid complications during the surgery and to reduce patient’s recovery time. Most of the minimally invasive surgeries are operated using robots. For avoiding the tremors during the procedure while operating with robots, Luo et al. (2018) presented a method for attenuating the tremors using machine learning. The proposed method is based on optimizing parameters using particle swarm optimization technique and building a hybrid support vector machine with an integrated kernel to attenuate tremors. Stapedotomy is a surgical procedure performed to improve hearing, which requires the estimation of the thickness of the stapes bone, which is usually done by drilling a hole through the bone. Kaburlasos et al. (1999) used machine learning techniques for the estimation of thickness. For the estimation, the author used a machine learning scheme known as Fuzzy Lattice Neurocomputing. In complex trauma surgeries, the surgeons are using augmented reality to understand the relationship between anatomy, tools, and implants. Olivier Pauly et al. (2015) proposed a model to improve surgical scene understanding using augmented reality. For this work, the random forest was used to identify objects in the scene, and the pixel-wise alpha map was created using an object-specific lookup table for image fusion. The data for this model is obtained from the C-arm devices with the Kinect RGB-Depth sensor. Napolitano et al. (2016) used machine learning algorithms like K-nearest neighbor, naive Bayes, and perceptron algorithm with uneven margins to classify semi-structured and unstructured pathology reports. He highlighted that the K-nearest neighbor algorithm built with binary occurrence type word vector, stop word filter, and pruning produced high accuracy in classifying semi-structured reports.

3.4. Cardiology

Cardiovascular diseases are life-threatening diseases that require a high degree of accuracy and precision for their diagnosis. Machine learning has increased the rate of accuracy in diagnosing diseases. Hijazi et al. (2016) described the use of machine learning to monitor patients having cardiovascular diseases. The application of Deep neural networks to detect myocardial infarction (heart attack) from Electrocardiogram (ECG) signals was proposed by Acharya et al. (2017). The neural network used for this work consists of 11 convolution layers out of which six layers are activated by Rectified Linear Unit (ReLU) activation function, and the last layer is activated with soft-max function, the pooling function used is Max-pooling. The evaluation of results is done for both noisy and noiseless beat signals in the dataset. A novel approach was proposed by Peshala Tabassian et al. (2018) to detect heart failure with preserved ejection fraction by using a statistical model along with a supervised algorithm. The data for this work is preprocessing using the KNNimpute approach, and three principal component analysis models were built for the spatiotemporal representation of rest and exercise, and distance weighted nearest neigh-
A comparative analysis was performed by [Alić et al. (2017)] in using machine learning network structures to diagnose diabetes and cardiovascular diseases. According to this analysis, the network built using the Levenberg-Marquardt learning algorithm (LMLA) and Naïve Bayes network achieved better accuracy compared with other proposed models considered from 2008 to 2017. Hypertrophic cardiomyopathy (HCM) is a chronic heart disease that leads to the thickening of the heart muscle and restricts the flow of blood. [Rahman et al. (2015)] proposed a methodology to detect hypertrophic cardiomyopathy from 10 seconds, 12-lead electrocardiogram (ECG) signals. For this work, features are selected using information gain criterion, and random forest, and support vector machines are used for classification. The application of machine learning techniques to diagnose heart disease in patients is proposed by [Dinesh et al. (2018)]. The data for this work is preprocessed to make it suitable for classification. A set of five machine learning algorithms like logistic regression, random forest, gradient boosting, support vector machine, and naïve Bayes are used to make classification’s on the data. The accuracies of these classifiers are mentioned in table 4, out of which logistic regression has maximum accuracy. An ensemble learning methodology was proposed by [Chowdary et al. (2020)] to diagnose heart diseases. This methodology is based on the ensemble voting of Logistic Regression, artificial neural network, Gaussian naïve Bayes, random forest, and K-nearest neighbor algorithms. Their model achieved an accuracy of 89%, precision of 91.6%, sensitivity of 86%, and specificity of 91%. Atherosclerosis is the primary factor for cardiovascular diseases like a heart attack. A novel methodology was proposed by [Xie et al. (2017)], which focuses on the detection of risk factors from the different stages of carotid atherosclerosis that are leading to cardiovascular diseases. This method focuses on the use of a decision tree algorithm with a neural network, logistic regression, and support vector machine for making accurate predictions. Seismocardiographic signals are used to study cardiopulmonary interactions. [Gamage et al. (2018)] used k-means clustering along with a time-domain amplitude feature to cluster Seismocardiographic signals. Single-photon emission computed tomography (SPET) imaging is a nuclear imaging technique used to capture the functioning of the heart using gamma rays. [Betancur et al. (2018)] used machine learning to combine clinical information and SPET imaging data to predict major adverse cardiac events (MACE). The use of machine learning for rehabilitation assessment is proposed by [Prochazka et al. (2018)]. Thermal and heart rate data is processed, and the Neural network with sigmoidal and probabilistic transfer function is used for the assessment.

### 3.5. Pulmonology

Respiratory diseases are very complex diseases that affect not only the lungs but also the other organs of the body. Predicting these diseases in advance can reduce the complications while treating these diseases. Many studies are performed by researchers in diagnosing respiratory diseases by using machine learning techniques. Acute diseases like Respiratory distress syndrome (ARDS) is diagnosed using machine learning by [Reameroon et al. (2018)]. For this work, four different versions of the Support vector machine were built. The performance of these algorithms is evaluated based on accuracy and area under the receiver operating characteristic (ROC) curve shown in table 5. Audio auscultation is the primary examination that a specialist performs when he sees a patient. Audio auscultation is considered to be the best primary practice to detect abnormalities in the heart and lungs. An approach was performed by [Chambres et al. (2018)] to detect respiratory diseases using audio auscultation. In this approach, the automatic free sound extractor was used to extract features from the ICBHI-2017 challenge database, and a boosted decision tree algorithm is used to detect sounds with respiratory diseases. A study was performed by [Palaniappan et al. (2014)] in diagnosing respiratory pathologies from pulmonary acoustic signals using support vector machine and K-nearest neighbor algorithms. A comparative study was performed by [Sadr and de Chazal (2016)] to detect obstructive sleep apnoea by using electrocardiogram (ECG) and respiratory chest signals. Three models, namely Support Vector machine, linear discriminant analysis, and extreme learning machine was built. These three models diagnosed the disease with high accuracy when they are trained with respiratory chest signals. Seismocardiogram cycles were used to identify respiratory phases like inspiration and expiration using machine learning by [Zakeri and Tavakolian (2015)]. For building, this model support vector machine was employed and trained with the 50 percent data approved by healthcare

| Author                | Methods                                      | Diagnosis/Application                                      | Metrics                          | Findings  |
|-----------------------|----------------------------------------------|------------------------------------------------------------|----------------------------------|-----------|
| Kobashi et al. 2016   | Statistical Kinematics model                 | Understanding the function of knee implants after the surgery | mean correlation coefficients    | 0.79      |
|                       |                                              |                                                            | mean root-mean-squared-error     | 3.44 mm   |
| Napolitano et al. 2016| K-nearest neighbour algorithm with binary occurrence type word vector, stop word filter and pruning | Classification of unstructured pathology repository          | Accuracy                        | 99.4%     |
Table 4. ML and DL methods in Cardiology.

| Author               | Method                                                                 | Diagnosis/Application                  | Metric                  | Findings                        |
|----------------------|------------------------------------------------------------------------|----------------------------------------|-------------------------|---------------------------------|
| Acharya et al. (2017)| Convolutional Neural Network                                           | Myocardial infarction                  | Accuracy                | noisy beats: 93.53 noiseless beats: 95.22 |
|                      |                                                                        |                                        | Sensitivity             | noisy beats: 93.71 noiseless beats: 95.49 |
|                      |                                                                        |                                        | Specificity             | noisy beats: 92.83 noiseless beats: 94.19 |
| Tabassian et al. (2018)| Statistical model and Distance-weighted -nearest-neighbor (DWNN)    | Heart failure                          | Sensitivity             | 86%                             |
|                      |                                                                        |                                        | Specificity             | 82%                             |
|                      |                                                                        |                                        | Area under ROC Curve     | 0.89                            |
|                      |                                                                        |                                        | Accuracy                | 85%                             |
| Alić et al. (2017)   | Multilayer feedforward neural network with Levenberg-Marquardt learning algorithm. | Diabetes and cardiovascular disease in general | Accuracy                | 87.29% (diabetes)               |
|                      |                                                                        |                                        |                         | 89.38% (Cardio Vascular Disease) |
|                      |                                                                        |                                        |                         | 99.51% (diabetes)               |
|                      |                                                                        |                                        |                         | 97.52% (Cardio Vascular Disease)|
| Rahman et al. (2015)| For Random Forest and Support Vector Machine                         | Hypertrophic cardiomyopathy            | Precision                | 0.84                            |
|                      |                                                                        |                                        | Recall                  | 0.89                            |
|                      |                                                                        |                                        | Specificity             | 0.93                            |
|                      |                                                                        |                                        | F-Measure               | 0.86                            |
| Dinesh et al. (2018)| Logistic Regression, Random Forest, Naive Bayes, Gradient Boosting    | Heart disease in general               | Accuracy                | 0.8651685                       |
|                      |                                                                        |                                        |                         | 0.8089888                      |
|                      |                                                                        |                                        |                         | 0.8426966                       |
|                      |                                                                        |                                        |                         | 0.7977528                      |
| Chowdary et al. (2020)| Ensemble Voting of Logistic regression, artificial neural network, gaussian naive bays, random forest and K-nearest neighbor. | Heart disease in general               | Accuracy                | 89%                             |
|                      |                                                                        |                                        | Precision               | 91.6%                           |
|                      |                                                                        |                                        | Sensitivity             | 86%                             |
|                      |                                                                        |                                        | Specificity             | 91%                             |
| Xie et al. (2017)    | Decision Tree algorithm with support vector machine, logical regression and neural networks | Carotid atherosclerosis              | Accuracy                | 87.2%                           |

3.6. Orthopaedics

The risk of having diseases like osteoporosis, arthritis is predicted using machine learning. A methodology was proposed by [Kim et al. (2013)] for the risk assessment of osteoporosis. In this methodology, the Support Vector machine is used for risk assessment, and this method was tested on the Korean government’s Survey’s dataset. The diagnosis of rheumatoid arthritis from X-ray images was proposed by [Morita et al. (2017)]. Support Vector Machine, along with a histogram of oriented gradients, is used for the diagnosis. The accuracy of the model detecting finger joints, erosion estimation, and Joint space narrowing (JSN) is shown in Table 6. The assessment of bone density from X-ray images was proposed by [Bian and Zhang (2018)]. In the proposed methodology, the traditional GoogleNet convolutional neural network was modified by adding large number filters with a multilayer perceptron. This modified neural network produced better results than the traditional neural network.

3.7. Radiology

Radiology deals with accurate, precise diagnosis and treatment of many diseases. Machine learning algorithms were used by [Lin et al. (2008)] for gating and tracking of lung cancer tumors. In this work, Principle component analysis and neural network with backpropagation algorithm are used for gating, and an artificial neural network is used for tracking. The results are shown in Table 7. [Tataru et al. (2017)] compared the performance of three convolutional neural network architectures namely GoogleNet, InceptionV3, and ResNet50 to detect abnormalities in a chest X-ray. For this work, the images from the Stanford Normal Radiology Diagnostic Dataset are used and are preprocessed using histogram equalization before training the CNN models. Detecting fractured bones from X-ray images was proposed by [Cao et al. (2015)]. For this work, many types of features were fused for building a stacked random forest model to detect the fractures of bones. This stacked random forest showed enhanced performance compared to the support vector machine. Machine learning classifiers and active learning methods are used by [Nguyen and Patrick (2014)], to classify radiology reports. In this work, four active learning methods like Self-Confident, Simple, Balance EE, and Kernel Farthest-First are analyzed to enhance the performance of the Support vector machine classifier for the classification of reports. The rule-based preprocessing method is used to preprocess the data. A study was performed by [Wei et al. (2005)] on using machine learning for the classification of Malignant and Benign
### Table 5. ML and DL methods in Pulmonology.

| Author                  | Method                                                                 | Disease                        | Metrics          | Findings         |
|-------------------------|------------------------------------------------------------------------|--------------------------------|------------------|------------------|
| Reamaroon et al. 2018   | Support Vector Machine with a class weighted cost function Sampled Randomly | Respiratory distress syndrome  | Accuracy 0.7478  |                  |
|                         | Support Vector Machine with a class weighted cost function without any sampling |                                | Area under ROC Curve 0.7703 |                  |
|                         | Support Vector Machine with Label Uncertainty sampled randomly         |                                | Accuracy 0.7698  |                  |
|                         | Support Vector Machine with Label Uncertainty without any sampling     |                                | Area under ROC Curve 0.7989 |                  |
| Chambres et al. 2018    | Boosted Decision Tree                                                  | Respiratory abnormalities from audio auscultation | Accuracy 85%   |
| Zakeri and Tavakolian 2015 | Support Vector Machine                                    | Respiratory phase identification (inspiration and expiration) | Accuracy 88.4%  |
| Gerard et al. 2018      | FissureNet (Coarse to fine cascade of two Seg3DNets)                 | Pulmonary fissure              | Area under the precision recall curve 0.991 |

### Table 6. ML and DL methods in Orthopaedics.

| Author                  | Method                                               | Diagnosis/Application                   | Metric           | Findings         |
|-------------------------|------------------------------------------------------|----------------------------------------|------------------|------------------|
| Kim et al. 2013         | Support Vector Machine                               | Risk assessment of osteoporosis        | Area under ROC Curve 0.827 |                  |
|                         |                                                       |                                        | Accuracy 76.7%   |                  |
|                         |                                                       |                                        | Sensitivity 77.8%|                  |
|                         |                                                       |                                        | Specificity 76.0%|                  |
| Morita et al. 2017      | Support Vector Machine                               | Rheumatoid arthritis                  | Accuracy 81.4%   | (detection of finger joints) |
|                         |                                                       |                                        | 50.09            | (erosion estimation) |
|                         |                                                       |                                        | 64.3% (JSN score) |                  |
| Bian and Zhang 2018     | Modified GoogleNet convolution neural network         | Bone density assessment               | Accuracy         | 91.3%           |
Five freely available networks from the Caffe library are used for detecting microcalcifications. In this work, five different machine learning and deep learning algorithms, namely Support Vector Machine, Kernel Fisher Discriminant, Relevance Vector Machines, Feed Forward Neural Network, and Ada Boost, were studied and their performances were evaluated. The performances of the classifiers are described in table 7. Wu et al. (1993) used machine-learned features to detect breast cancer from mammograms. For this approach, a three-layered feedforward neural network with a backpropagation algorithm was used to detect breast cancer. This neural network is trained on features extracted from mammograms by experienced radiologists. Abnormalities from orthopedic trauma radiographs are diagnosed using neural network approaches by Jakub Olczak et al. (2017). Five freely available networks from the Caffe library are considered, and they are retrained with 13 epochs. The performance of all the networks is similar and exhibited an accuracy of 90%

### 3.8. General medicine

Computer-aided diagnosis is used in general medicine to diagnose diseases based on the symptoms of the patient. The Survey of machine learning models in general medicine is shown in Table 9. A machine learning approach was proposed by ? to improve the performance of computer-based diagnosis systems. For this purpose, a semi-supervised learning algorithm named co-forest was used. Mulyani et al. (2016) proposed a model to diagnose fever. This model was built using the Naive Bayes algorithm with Dempster Shafer theory. Dengue hemorrhagic fever is a fatal disease that was found mostly in the southern parts of Asia. For estimating the risk level of this disease, a machine learning model was proposed by Najar et al. (2018). The risk level of the disease is predicted using an extreme learning machine. For avoiding aspiration pneumonia, a swallowing assessment model was developed using machine learning techniques by Inoue et al. (2018). The features are extracted using linear predictive coding, and a support vector machine is used to classify patients with dysphagia. Convolutional neural networks were used by Liang et al. (2016) to diagnose malaria. The performance of the neural network is superior to the performance of the support vector machine.

### 3.9. Oncology

Diseases like cancer need accurate prediction for their diagnosis and treatment. A comparative study was performed by Shetty and Shah (2018) on using machine learning to diagnose cervical cancers. Various existing machine learning models were analyzed in this study. Turkci (2018) performed an analysis of using machine learning for diagnosing cancer. Machine learning techniques like Xgboost, Deepboost, Boostsl, and support vector machine are studied. The performances of these algorithms were shown in table 8. A model was proposed by Lambrou et al. (2009) to diagnose breast cancer using a genetic algorithm. This genetic algorithm obtained an accuracy of 97.2. The detection of colon cancer from CT colonography images was proposed by Godkhindi and Gowda (2017). A histogram of oriented gradients is employed to extract features, and a fully connected neural network was used for diagnosis. Convolutional neural networks performed better than other existing algorithms for diagnosis. Many cancer-related deaths are due to prostate cancer. A neural network model was developed by Tsehay et al. (2017) to detect prostate cancers from multi-parametric MRI scan images. This convolutional neural network has 5 convolutional layers, and it is evaluated based on the area under the ROC curve. Machine learning and deep learning techniques are applied to classify cancerous profiles by Sharma and Rani (2017). For this work, a feedforward neural network with a backpropagation algorithm and support vector machine is used for clustering and classification of data. Neural network approaches were used by Ausawalaithong et al. (2018) to detect lung cancer from chest x-ray images. For this work, 121 layered neural network and transfer learning methods are employed for building the model. The performance of the model over three different datasets are shown in Table 8. The waiting times of patients in radiological oncology were predicted using machine learning techniques by Joseph et al. (2017a). For this study, a set of four different algorithms, namely, support vector machine, linear regression, random forest, and decision tree, were analyzed. Random Forest algorithm performed best when compared to the remaining three algorithms.

### 3.10. Psychiatry

Psychiatric disorders are common health problems with which millions of people are suffering around the world. Machine learning and deep learning helps to diagnose problems like depression based on data from many sources. The models surveyed to diagnose psychiatric disorders are shown in Table 10. An approach was proposed by Wongkoblap et al. (2017) to classify people with depression based on the data from social networking sites. A multilayer neural network was used for the classification of users with depression from social network data. Another methodology was proposed by Arun et al. (2018) to classify depression using deep learning. For this method, the particle swarm optimization algorithm is used for feature extraction, and Meta Cognitive neural network with projection-based learning is used for classification. A study was performed by Sahoo et al. (2020) to diagnose depression using machine learning in diabetes mellitus type 2 patients. For this study, four machine learning algorithms, namely the K-means, Fuzzy C-mean, probabilistic neural network, and support vector machine, were built. The performance of the Support vector machine is better compared to the remaining algorithms. For the detection of stress, a machine learning framework was proposed by Subhani et al. (2017). Stress at different levels was diagnosed from Electrocardiogram signals using a logistic regression model. Psychiatric disorders are found in newborn babies, which were inherited from their depressed parents. A study was performed by Liu et al. (2017) to detect familiar depression in patients from MRI scans using machine learning and deep learning. In this study, logistic regression, graph convolutional neural network, and Support vector machine were analyzed. Various machine learning algorithms were compared by Sau and Bhakti (2019) to diagnose depression and anxiety among patients. Five different classifiers, namely Logistic Regression, Random Forest, CatBoost, Naive Bayes, and Support
### Table 7. ML and DL methods in Radiology.

| Author            | Method                                      | Application/Diagnosis                  | Metrics                  | Findings  |
|-------------------|---------------------------------------------|----------------------------------------|--------------------------|-----------|
| Lin et al. (2008) | Principal Component Analysis and Artificial Neural Network (Gating) | Gating and tracking of lung cancer tumours | Precision 96.5          |           |
|                   | Artificial Neural Network (tracking)        |                                        | mean localization error 2.1 pixels |           |
|                   |                                              |                                        | maximum error at 95% confidence level 4.6 pixels |           |
| Tataru et al. (2017) | CNN with GoogLeNet architecture  | Abnormality detection of chest x-ray | Accuracy 0.8            |           |
| cite{61}          | Stacked Random Forests Feature fusion.      |                                        | F1 Score 0.66           |           |
| Nguyen and Patrick (2014) | Support Vector Machine  | Classification of radiology reports | Sensitivity 98.25%      |           |
|                   |                                              |                                        | Specificity 96.14%      |           |
| Wei et al. (2005) | Support Vector Machine                        | Malignant and Benign microcalcifications | Standard Deviation 0.0259 |           |
|                   | Kernel Fisher Discriminant                   |                                        | Standard Deviation 0.0254 |           |
|                   | Relevance Vector Machines                    |                                        | Standard Deviation 0.0243 |           |
|                   | Feed Forward Neural Network                  |                                        | Standard Deviation 0.0266 |           |
|                   | Ada Boost                                    |                                        | Standard Deviation 0.0268 |           |
| Wu et al. (1993)  | Artificial Neural network                   | Breast cancer                         | Area under ROC Curve 1  |           |

### Table 8. ML and DL methods in General Medicine.

| Author            | Method                                      | Application/Diagnosis                  | Metric                  | Findings  |
|-------------------|---------------------------------------------|----------------------------------------|--------------------------|-----------|
| Mulyani et al. (2016) | Dempster Shafer with Naive Bayes | Fever | Accuracy | 56.25% |
| Najar et al. (2018) | Extreme learning machine                  | Dengue Hemorrhagic Fever               | Mean Absolute Error 0.08698 |           |
|                   |                                              |                                        | Mean Absolute Percentage Error 3.00536 |           |
| Inoue et al. (2018) | Support Vector Machine with Linear predictive coding | Dysphagia | Sensitivity 82.4% | 100% |
|                   |                                              |                                        | Specificity 86%          |           |
| Liang et al. (2016) | Convolutional neural network                | Malaria                               | Accuracy 97.37%         |           |
|                   |                                              |                                        | Sensitivity 96.99%       |           |
|                   |                                              |                                        | Specificity 97.75%       |           |
|                   |                                              |                                        | F1-Score 97.36%          |           |
|                   |                                              |                                        | Precision 97.73%         |           |
|                   |                                              |                                        | Matthews correlation coefficient 94.75% |           |
| Author          | Method                      | Diagnosis/Application                                                                 | Metrics                                      | Findings                                                                 |
|-----------------|-----------------------------|----------------------------------------------------------------------------------------|----------------------------------------------|--------------------------------------------------------------------------|
| **Turki (2018)**| Xgboost                     | Thyroid cancer, colon cancer and liver cancer                                           | Average mean area under Curve                | Thyroid nodule: 0.811<br>Colon: 0.872<br>Liver: 0.797                  |
|                 |                             |                                                                                       | AMACC                                        | Thyroid nodule: 0.798<br>Colon: 0.857<br>Liver: 0.775                  |
|                 | Support Vector Machine      |                                                                                        | Average mean area under Curve                | Thyroid nodule: 0.750<br>Colon: 0.897<br>Liver: 0.897                  |
|                 |                             |                                                                                        | AMACC                                        | Thyroid nodule: 0.726<br>Colon: 0.890<br>Liver: 0.895                  |
|                 | DeepBoost                   |                                                                                        | Average mean area under Curve                | Thyroid nodule: 0.758<br>Colon: 0.822<br>Liver: 0.791                  |
|                 |                             |                                                                                        | AMACC                                        | Thyroid nodule: 0.744<br>Colon: 0.833<br>Liver: 0.786                  |
|                 | Boost I                     |                                                                                        | Average mean area under Curve                | Thyroid nodule: 0.500<br>Colon: 0.500<br>Liver: 0.500                  |
|                 |                             |                                                                                        | AMACC                                        | Thyroid nodule: 0.658<br>Colon: 0.694<br>Liver: 0.652                  |
| **Lambrou et al. (2009)** | Genetic Algorithm          | Breast cancer                                                                          | Accuracy                                     | 97.2%                                                                    |
| **Godkhindi and Gowda (2017)** | Convolutional Neural Network | Colon cancer                                                                           | Accuracy                                     | Colon detection: 87.03%<br>Polyp Detection In colon: 88.56<br>Sensitivity<br>Polyp Detection In Colon: 88.77%<br>Specificity<br>Polyp Detection In Colon: 87.35% |
| **cite[70]**     | Deep Convolutional Neural Network | Prostate cancer                                                                       | Area under ROC Curve                         | 0.903±0.009                                                             |
| **Sharma and Rani (2017)** | Feed Forward Network and (clustering) Support Vector Machine(classification) | Cancer profile classification                                                             | Accuracy                                     | 87.51 (for 100 samples)<br>Accuracy 93.57 (for 100 samples)           |
| **Ausawalaithong et al. (2018)** | 121-layer Densely Connected Convolutional Network | Lung cancer                                                                           | Mean Accuracy                                | 74.43±0.61%                                                            |
| **Joseph et al. (2017a)** | Random Forest Regressor     | Prediction of patients waiting time                                                     | Mean Absolute Error [min]                    | 3.3                                                                     |
|                 |                             |                                                                                        | Mean Absolute Error [min]                    | 4.6                                                                     |
|                 |                             |                                                                                        | Standard Deviation Error [min]               | 6.1                                                                     |
|                 |                             |                                                                                        | R-squared                                    | 0.47                                                                    |
Vector machine, were evaluated. A comprehensive survey was performed by Panicker and Gayathri (2019) on using machine learning to build systems that detect mental stress. In this survey, popular feature selection methods are discussed. A comparative study was performed by Garcia-Ceja et al. (2018) on using random forest and neural networks to classify depression in patients based on motor activity. The performance of random forest is better when compared to the neural network. A hybrid model was developed by Heraz et al. (2007) to predict the emotional state of learners from brain waves using machine learning techniques. WEKA software is used for this approach, and the emotional states were predicted using the K-nearest neighbor algorithm.

3.11. Endocrinology

3.11.1. Diabetes

Diabetes is a major cause of many deadly diseases like cardiovascular diseases, brain strokes, and many more. The observations from surveyed papers are recorded in Table 11. An approach was proposed by Dutta et al. (2018) to diagnose diabetes using machine learning. For this approach, a random forest classifier was used, and its performance was superior compared with logistic regression and support vector machine. A study was performed by Stoean et al. (2006) to diagnose diabetes mellitus using a support vector machine. For this study, linear and non-linear support vector machines were analyzed and tested on a standard dataset from the UCI repository. A study was performed by Allassaf et al. (2018) on using machine learning for preemptive diagnosis of diabetes mellitus. In this study, four machine learning algorithms, namely naive Bayes, k-nearest neighbor, support vector machine, and neural network, were analyzed. Artificial neural networks outperformed all the remaining three classifiers. Using a Support vector machine with radial bias function(RBF) kernel for diagnosing diabetes mellitus was proposed by Barakat et al. (2010). For this work, the data is sampled using a K-means clustering algorithm. An approach was proposed by Tamin and Iswari (2017) to predict the rate of re-admission of diabetes mellitus patients at the hospital. C.45 algorithm is used for prediction on a standard dataset from the UCI machine learning repository.

3.11.2. Thyroid

A comparative study was performed by Maysanjaya et al. (2015) to diagnose thyroid disease. In his study, he analyzed six models, namely perceptron network, a neural network with Radial based function(RBF) kernel, artificial immune recognition system, Learning Vector Quantization, and feedforward network with backpropagation algorithm. The performance of these models is shown in Table 12. Classifying the type of thyroid using machine learning was proposed by Ahmed and Soomrani (2016). A support vector machine classifier is used to make classifications on the real-time data obtained from the UCI repository and a well-known hospital in Pakistan. The segmentation and classification of thyroid images from ultrasound scans were proposed by Selvathi and Sharnitha (2011). For this model, the Extreme learning machine and support vector machine is used for segmentation and classification of ultrasound images. The performance of these models is shown in Table 12.

3.12. Neurology

Machine learning and deep learning methods are used in neurology to diagnose neurological disorders at an early stage. The performance of the models used to diagnose neurological disorders is shown in Table 13. The diagnosis of chronic diseases like schizophrenia from MRI scans was proposed by Nimkar and Kuball (2018). For this approach, the Boruta algorithm is used for feature selection, and various machine learning algorithms were built, namely Support vector machine, Linear discriminant analysis, Naive Bayes, K-nearest neighbor, C5.0 Decision tree, Gaussian process classifier, and random forest. A method was proposed by Zhang and Wang (2007) to classify normal and abnormal brain Computed Tomography(CT) scan images. The features for this approach were extracted based on greyscale, shape and texture, symmetric features. See5 and Neural network with radial bias function was built based on these features. Cerebral microbleeds are chronic brain hemorrhages that lead to the death of a person. The diagnosis of cerebral microbleeds from Susceptibility weighted imaging(SWI) scans using deep learning was proposed by Lu et al. (2017). Eight layered Convolutional neural network model was built and trained with 8000 images for diagnosis. An approach was proposed by Cole et al. (2014) to recognize and anticipate the seriousness of tremor and dyskinesia using machine learning and deep learning methods. For this work three models namely the hidden Markov model, support vector machines, and neural networks, were built for the detection of tremors and dyskinesia. The seriousness of tremor and dyskinesia was anticipated using the Bayesian maximum likelihood classifier. A diagnostic approach for dementia and mild cognitive impairment using machine learning was proposed by Daniel Stamate et al. (2018). For this approach three models namely extreme gradient boosting, stochastic gradient boosting, and the random forest was built using the features extracted by the ReliefF method. A two-step approach for classifying Parkinson’s disease gait was proposed by Wahid et al. (2015). In this approach, the first step is to normalize the data using a multi regression approach, and the second step is classification using random forest. The performance of this approach is superior to the performance of the support vector machine and kernel Fisher discriminant. The detection of epileptic convulsions from accelerometric signals using machine learning was proposed by Mlodesvic et al. (2014). For this work, the classification of seizure and non-seizure epochs is done using the least-square support vector machine. The data for this work is collected from the patients using four accelerometers tied to their wrists and ankles. Eskofier et al. (2016) proposed a neural network model for the assessment of Parkinson’s disease. For this work convolutional neural network with a rectified linear unit(ReLU) activation function was built, and it showed better performance compared to K-nearest neighbor, support vector machine, AdaBoost, and partial decision tree. Bradykinesia is an important factor in the diagnosis of Parkinson’s disease. A method was proposed by Martinez-Manzanera et al. (2015) to predict the scores of each patient based on their moments using a support vector machine. Movements like finger tapping, diadochokinesis, and toe-tapping were considered.
### Table 10. ML and DL methods in Psychiatry.

| Author               | Algorithm                                                                 | Application/Diagnosis                  | Metrics       | Findings                           |
|----------------------|----------------------------------------------------------------------------|----------------------------------------|---------------|------------------------------------|
| Arun et al. 2018     | Meta-Cognitive Neural Network using Projection-based learning framework and particle swarm optimization | Classification of depression           | Efficiency    | 85.94% (Average)                  |
|                      |                                                                           |                                        | Sensitivity   | 94.4% (Overall)                    |
|                      |                                                                           |                                        | Sensitivity   | 89.4% (Average)                    |
|                      |                                                                           |                                        | Sensitivity   | 96.5% (Average)                    |
| Sahoo et al. 2020    | Support Vector Machine                                                    | Depression                             | Accuracy      | 96.475                            |
|                      | Fuzzy C-MEAN                                                              |            | 95.455                     |
|                      | Probabilistic Neural Network                                              |            | 93.75                      |
|                      | K-Means                                                                   |            | 87.879                     |
| Subhani et al. 2017  | Logistic Regression Classifier                                            | Stress                                  | Accuracy      | 94.6% for two level identification |
|                      |                                                                           |                                        |               | 83.4% for multilevel identification |
| Liu et al. 2017      | Logistic Regression with regularisation                                    | Familiar depression                     | Accuracy      | 97.78%                            |
|                      | Support Vector Machine                                                    |            | 93.67%                     |
|                      | Graph convolution neural network                                          |            | 89.58%                     |
| Sau and Bhaka 2019   | CatBoost                                                                  | Depression and anxiety                  | Accuracy      | 89.3%                             |
|                      | Logistic Regression                                                       |            | 87.7%                      |
|                      | Support Vector Machine                                                    |            | 82.1%                      |
|                      | Naive Bayes                                                               |            | 82.1%                      |
|                      | Random Forest                                                             |            | 78.6%                      |
| Panicker and Gayatri 2019 | Random Forest                              | Stress                                  | F1-Score      | 73%                              |
|                      |                                                                           |                                        | Matthews correlation coefficient | 0.44        |
|                      |                                                                           |                                        | Matthews correlation coefficient | 0.35        |
| Garcia-Ceja et al. 2018 | K-Nearest Neighbour                                   | Depression                             | Precision     | 79.2% - 84%                      |
|                      |                                                                           |                                        | Recall         | 78.7% - 82.2%                    |
|                      |                                                                           |                                        | F-Measure      | 79.2% - 83.5%                    |
|                      |                                                                           |                                        | KAPPA          | 0.78                             |
|                      |                                                                           |                                        | Sensitivity    | 82.27%                           |

### Table 11. ML and DL methods in Endocrinology (Diabetes).

| Author               | Method                        | Diagnosis/Application                  | Metric      | Findings |
|----------------------|-------------------------------|----------------------------------------|-------------|----------|
| Dutta et al. 2018    | Random Forest                 | Diabetes                               | Accuracy    | 84%      |
| Stoean et al. 2006   | Support Vector Machine        | Diabetes mellitus                      | Accuracy    | 80.20%   |
| Allassaf et al. 2018 | Artificial Neural Network     | Diabetes mellitus                      | Accuracy    | 77.50%   |
|                      | Support Vector Machine        |                                        | 71.25       |
|                      | K-Nearest Neighbor            |                                        | 73.75%      |
|                      | Naive Bayes                   |                                        | 67.5%       |
| Barakat et al. 2010  | Support Vector Machine        | Diabetes mellitus                      | Accuracy    | 94%      |
|                      |                              |                                        | Sensitivity | 93%      |
|                      |                              |                                        | Specificity | 94%      |
| Tamin and Iswari 2017| C4.5 Algorithm                | Prediction readmission rate of diabetes patients at hospitals | Accuracy    | 74.5%    |
Classifying neurological gait disorders like Parkinson’s disease and stroke using multi-task feature learning was proposed by Papavasileiou et al. (2017). For building this multi-task feature learning method, a support vector machine and neural network were used. The segmentation of glioblastomas from brain MRI scans was proposed by Joseph et al. (2017b). The proposed method focuses on replacing manual segmentation of brain MRI scans with automated segmentation using machine learning. In this approach, segmentation is done using K-means clustering, and the segmentation accuracy of this model is better than the accuracy of manual segmentation. The detection of chronic traumatic Encephalopathy using machine learning was performed by Louis et al. (2017). For this work, Random classifier, Random Forest, Support vector machine(RBF kernel), and K-nearest neighbor, were built. These models were trained with data from two sequences, namely PRESS and L-COSY of magnetic resonance spectroscopy. The accuracy of the classifiers is better when they are trained with L-COSY.

3.13. Dermatology

The diagnosis of dermatological diseases using machine learning and deep learning was proposed by Kumar et al. (2016). Three machine learning models, namely neural networks, decision tree, and an nth nearest neighbor were built and trained using a standard dataset. An approach was performed by Arifin et al. (2012) to diagnose skin diseases from colored images using artificial neural networks. Various methods, like image cropping and color gradient generation, are applied to preprocess the data. A feedforward neural network with a backpropagation algorithm was used for diagnosis. The segmentation of skin ulcer images using machine learning was proposed by Seixas et al. (2015). In this study, several models like Extreme learning machine, J48, Support vector machine, K-nearest neighbor, Random Forest, Multilayer perceptron, and Naive Bayes were analyzed. The performance of these algorithms in the segmentation of ulcers is shown in table 14. A survey was performed by Hegde et al. (2018) on using machine learning algorithms for classifying skin diseases based on color and texture features. For this survey, skin diseases, namely Eczema, Lichen plants, and plague psoriasis, were diagnosed using linear discriminant analysis, artificial neural networks, naive Bayes, and support vector machine. A novel method was proposed by Lahijanian et al. (2016) to diagnose erythematous-squamous diseases using ensemble modeling. Support vector machine, multilayer perceptron, and k-nearest neighbor algorithms were built using the features extracted based on rough set theory. The results of these algorithms were combined using the majority voting method(Ensemble method). The diagnosis of diseases, namely melanocytes nevus, seborrheic keratosis, basal cell carcinoma, and psoriasis using neural network approaches were proposed by Zhang et al. (2017). In this approach, transfer learning of GoogleNet InceptionV3 is used for diagnosis. For this approach, two different datasets with the same diseases and features were used to train the model. The early diagnosis of skin tumors is possible by estimating the constituent elements of the skin. An approach was proposed by Vyas et al. (2014) to estimate the skin elements using machine learning. The support vector regressor model was used for estimating skin constituents.

3.14. Hepatology

A comparative study of using machine learning techniques to diagnose the advanced stage of liver fibrosis in patients suffering from Hepatitis C was performed by Hashem et al. (2017). In this study, five machine learning algorithms were analyzed, namely alternating decision tree, particle swarm optimization, multi-linear regression, alternating decision tree with criterion point zero, and genetic algorithm. An approach was proposed by Nasr et al. (2017) to diagnose liver fibrosis from liver biopsies using machine learning and search algorithms. In this approach, Related Objects, Skipper algorithm is used to query the database, and a rule-based subsumption algorithm is used for diagnosis. Predicting the stage of liver fibrosis is essential for the treatment of the disease. Ayeldeen et al. (2015) proposed a methodology to predict the stage of liver fibrosis using machine learning. In this methodology, liver fibrosis is classified into five stages using a decision tree algorithm. A methodology was proposed by Cai et al. (2018) for predicting the stage of fibrosis and inflammatory activity from serum indices data of Hepatitis C patients using the Extreme learning machine algorithm.

3.15. Nephrology

The prediction of chronic kidney disease using machine learning was proposed by Charlemonan et al. (2016). For this
| Author                  | Method                                      | Diagnosis/Application                                      | Metrics          | Findings     |
|------------------------|---------------------------------------------|------------------------------------------------------------|------------------|--------------|
| Nimkar and Kubal (2018)| Support vector machine                      | Schizophrenia                                              | Accuracy         | 94.12%       |
|                        | C4.5 Decision tree                          |                                                            |                  | 91.18%       |
|                        | Random Forest                               |                                                            |                  | 79.41%       |
|                        | K-Nearest Neighbours                        |                                                            |                  | 79.41%       |
|                        | Linear discriminant analysis                |                                                            |                  | 92%          |
|                        | Gaussian process classifier (laplacedot)     |                                                            |                  | 85.29%       |
|                        | Naive Bayes                                 |                                                            |                  | 77%          |
| Zhang and Wang (2007)  | See5                                        | Brain abnormalities                                        | Accuracy         | 90%-94%      |
|                        | Radial Bayes Function Neural Network         |                                                            |                  | 77%-82%      |
| Lu et al. (2017)       | Convolutional neural network                | Cerebral microbleeds                                       | Sensitivity      | 97.29%       |
| Cole et al. (2014)     | Neural Network                              | Detection of tremor and dyskinesia                        | Global Error Rate| Tremor: 6.2% |
|                        |                                            |                                                            |                  | Dyskinesia: 8.8% |
|                        |                                            |                                                            |                  | Tremor: 7.2% |
|                        |                                            |                                                            |                  | Dyskinesia: 9.1% |
|                        |                                            |                                                            |                  | Tremor: 6.1% |
|                        |                                            |                                                            |                  | Dyskinesia: 12.3% |
|                        | Support Vector Machine                      |                                                            |                  |              |
|                        | Hidden Markov models                        |                                                            |                  |              |
|                        | Bayesian maximum likelihood classifier       | Seriousness of tremor and dyskinesia                       | Sensitivity      | Tremor: 96.3%|
|                        |                                            |                                                            |                  | Dyskinesia: 99.3% |
| Stamate et al. (2018)  | Extreme Gradient Boosting                   | Dementia and mild cognitive impairment                     | Accuracy         | 0.88         |
| Wahid et al. (2015)    | kernel Fisher discriminant                  | Parkinson’s disease                                        | Accuracy         | 86.2%        |
|                        | Support Vector Machine                      |                                                            |                  | 80.4%        |
|                        | Random Forest                               |                                                            |                  | 92.6%        |
| Milošević et al. (2014)| Least-squares support vector machine classifier| Epileptic convulsions                                     | Median sensitivity| 100%         |
|                        |                                            |                                                            |                  | (For seizures longer than 30 seconds) |
|                        |                                            |                                                            |                  | False detection rate |
|                        |                                            |                                                            |                  | 0.39 h-1     |
|                        |                                            |                                                            |                  | (For seizures longer than 30 seconds) |
| Eskofier et al. (2016) | Convolutional Neural Network                | Parkinson’s disease                                        | Accuracy         | 90.9         |
| Martinez-Manzanera et al. (2015) | Support Vector Machine | Parkinson’s disease                                      | Classification Errors | 15-16.5% (finger tapping) |
|                        |                                            |                                                            |                  | 9.3-9.8% (diadochokinesis) |
|                        |                                            |                                                            |                  | 18.2-20.2% (toe tapping) |
| Papavasileiou et al. (2017) | Multi Tasking Feature Learning               | Parkinson’s disease                                        | Area under ROC Curve | 0.96        |
| Joseph et al. (2017b)  | K-Means Clustering                          | Glioblastomas                                              | Dice Coefficient | 0.82321      |
| Louis et al. (2017)    | Random Classifier(L-COSY)                   | Chronic traumatic Encephalopathy                           | Accuracy         | 61%          |
|                        | Support Vector Machine-RBF(L-COSY)          |                                                            |                  | 38%          |
|                        | Random Forest(L-COSY)                       |                                                            |                  | 61%          |
|                        | K-Nearest Neighbours(L-COSY)                |                                                            |                  | 87%          |
|                        | Random Classifier(PRESS)                    |                                                            |                  | 45%          |
|                        | Support Vector Machine-RBF(PRESS)           |                                                            |                  | 60%          |
|                        | Random Forest(PRESS)                        |                                                            |                  | 70%          |
|                        | K-Nearest Neighbours(PRESS)                 |                                                            |                  | 75%          |
Table 14. ML and DL methods in Dermatology.

| Author                  | Method                              | Application/Diagnosis                                                                 | Metrics       | Findings                      |
|-------------------------|-------------------------------------|---------------------------------------------------------------------------------------|---------------|-------------------------------|
| Kumar et al. (2016)     | Decision Tree                       | Psoriasis, seborrheic dermatitis, lichen planus, pityriasis rosea, chronic dermatitis, pityriasis rubra pilaris | Accuracy      | 95%                           |
|                         | Neural Networks                     |                                         |               |                               |
|                         | Kth Nearest Neighbour               |                                         |               |                               |
| Arifin et al. 2012      | feed-forward back-propagation ANN    | Acne, eczema, psoriasis, tinea corporis, scabies and vitiligo                         | Accuracy      | 95.99% for diseases skin detection |
| Seixas et al. 2015      | Naive Bayes                         | Skin ulcer                              | Accuracy      |                               |
|                         | K-Nearest Neighbour                 |                                         |               |                               |
|                         | ELM                                 |                                         |               |                               |
|                         | Support Vector Machine              |                                         |               |                               |
|                         | J48                                 |                                         |               |                               |
|                         | Naive Bayes                         |                                         |               |                               |
|                         | Random Forest                       |                                         |               |                               |
|                         | Multi-Layer Perceptron              |                                         |               |                               |
| Hegde et al. 2018       | Artificial Neural Network           | Eczema, Lichen plants, and plaque psoriasis                                          | Accuracy      | 62.9                          |
|                         | Linear Discriminant Analysis        |                                         | Standard Deviation | 33.11 |
|                         | Naive Bayes                         |                                         | Accuracy      | 80.9                          |
|                         | Support Vector Machine              |                                         | Standard Deviation | 23.62 |
|                         | Random Forest                       |                                         | Accuracy      | 67.42                         |
|                         | Multi-Layer Perceptron              |                                         | Standard Deviation | 21.84 |
|                         | Standard Deviation                  |                                         | Accuracy      | 81.61                         |
| Lahijanian et al. 2016  | Majority voting of Multilayer       | Erythematosquamous                       | Accuracy      | 97.78%                        |
|                         | perceptron, K-Nearest Neighbour     |                                         |               |                               |
|                         | and Support Vector Machine          |                                         |               |                               |
| Zhang et al. 2017       | GoogleNet Inception v3 with transfer learning | Melanocytes nevus, seborrheic keratosis, basal cell carcinoma, and psoriasis      | Average accuracy | 86.54% |
|                         |                                     |                                         | Standard deviation | 3.63%  |
### Table 15. ML and DL methods in Hepatology.

| Author           | Method                                                                 | Diagnosis/Application | Metric       | Findings       |
|------------------|------------------------------------------------------------------------|------------------------|--------------|----------------|
| Hashem et al. (2017) | Multi-linear regression                                               | Liver fibrosis         | Accuracy     | 69.1%          |
|                  |                                                                        |                        | Sensitivity  | 69.0%          |
|                  |                                                                        |                        | Specificity  | 69.1%          |
|                  | Genetic Algorithms                                                     |                        | Accuracy     | 69.6%          |
|                  |                                                                        |                        | Sensitivity  | 68.9%          |
|                  |                                                                        |                        | Specificity  | 69.7%          |
|                  | Alternating decision tree                                              |                        | Accuracy     | 66.3%          |
|                  |                                                                        |                        | Sensitivity  | 73.0%          |
|                  |                                                                        |                        | Specificity  | 65.0%          |
|                  | Particle Swarm Optimization                                            |                        | Accuracy     | 66.4%          |
|                  |                                                                        |                        | Sensitivity  | 70.4%          |
|                  |                                                                        |                        | Specificity  | 65.6%          |
|                  | Alternating Decision Tree model with criteria point of zero            |                        | Accuracy     | 84.4%          |
|                  |                                                                        |                        | Sensitivity  | 70%            |
|                  |                                                                        |                        | Specificity  | 99%            |
| Nasr et al. (2017) | Related Objects Skipper algorithm with Subsumptions Rule-Based Classifier | Liver fibrosis         | Accuracy     | 99.48%         |
| Ayeldeen et al. (2015) | Decision Tree Classifier                                               | Liver fibrosis         | Accuracy     | 93.7%          |
| Cai et al. (2018)   | Extreme Learning machine                                              | Liver fibrosis and inflammatory activity | Accuracy | 69.11% (fibrosis stage) | 69.92% (inflammatory activity) |
work, four machine learning algorithms, namely support vector machine, decision tree, k-nearest neighbor, and logistic regression, were explored to find the best classifier. The support vector machine was found to be the best classifier. A methodology for the diagnosis of chronic kidney disease using a support vector machine was proposed by Wickramasinghe et al. (2017) to suggest the best diet plan for chronic kidney disease patients using machine learning. The best diet plan is recommended by this system by predicting the potassium zone of the patient. This experiment is carried out by various multi-class classifiers, namely decision tree, decision jungle, logistic regression, and neural network. Better performance was found in the decision tree. The surveyed models are tabulated in Table 16.

3.16. Ophthalmology

Grewal et al. (2018) and Ting et al. (2019) performed a study on using a convolutional network to detect ophthalmological diseases like cataract, glaucoma, and retinal disorders. Various models, namely decision tree, neural network, Naïve Bayes, and random forest, were analyzed by Malik et al. (2019) for detecting eye diseases. The performances of these algorithms are shown in table 18. From these algorithms, random forest and decision tree showed better performance. Vision impairing diseases like diabetic eye disease are major problems in today’s world. The diagnosis of diabetic eye disease from thermo-graphic images using machine learning is proposed by Selvathi and Suganya (2019). For this work, texture-based features are used by the support vector machine classifier for diagnosis. Exudates and hemorrhages are the two primary causes of diabetic retinopathy. The diagnosis of diabetic retinopathy from retinal scans was proposed by Senthakumar et al. (2016). For this approach, feature extraction and detection of hard exudates and hemorrhages from retinal images are done using principal component analysis and support vector machine. Das et al. (2019) proposed a method to detect Diabetic retinopathy and glaucoma from retinal images using a neural network framework. This work focuses on changing parametric values of the VGG 19 neural network for an accurate diagnosis.

3.17. Drug discovery

This section deals with the application of machine learning algorithms in the Pharma industry. Ongun et al. (2015) used machine learning for drug design. For this work, the prediction of inhibition of dihydrofolate reductase from pyrimidines is made using a support vector machine. The data for this research is taken from the University of California Irvine(UCI) machine learning repository. In this paper, the performance of Support Vector Machine is compared with the Prune network, multilayer perceptron(MLP) feedforward network, radial bias function network(RBF), dynamic network, and C5.0. The support vector machine performed best among the above algorithms with a training time of 93 seconds. Machine learning is used by Peter et al. (2012b) to predict proximal tubular toxicity in humans. For this work, the researchers developed a one-step protocol to differentiate human induced pluripotent stem cells(hiPCS) into proximal tubular like cells. A random forest algorithm is used for prediction. This algorithm is evaluated based on sensitivity, specificity, and accuracy and is shown in table 18. Drug likeness is predicted using machine learning by Khalaf et al. (2016b). In this work, Bayesian classifier, recursive portioning models were developed to predict the drug likeness, and these models are evaluated based on the compounds from the Traditional Chinese medicine compound database(TCMCD). Bayesian classifier with the LCFP,6 fingerprint set and physicochemical properties outperformed the Recursive partitioning model. A study was performed by Vamath-evan et al. (2019) on using machine learning and deep learning techniques in drug discovery. In this paper the authors surveyed the different machine learning and deep learning models that were used in target identification and validation, design and optimization of small molecules, discovery of biomarkers, prediction of drug sensitivity and in computational pathology.

3.18. COVID-19

ML and DL models play a prominent role in current pandemic situation, COVID-19. Researchers have done an extensive use of ML and DL methods for helping the healthcare professionals in diagnosing the disease through multiple sources ranging from X-rays till individual’s comorbidities. The authors have done a thorough literature study and the results obtained are shown in table 19. Hemdan et al. (2020) proposed a deep learning model named COVID-Net consisting of seven convolutional neural networks(CNN). This COVIDX-Net model diagnosed COVID-19 infection from x-ray images with an F1-score of 0.91. A deep learning open source model named COVID-Net was proposed by Wang et al. (2020) to diagnose COVID-19. This model was able to classify the x-ray images into three classes namely normal, Pneumonia, and COVID-19 with an accuracy of 92%. Apostolopoulos and Mpesiana (2020) performed a comparative study on using state-of-the-art deep learning architectures namely VGG19, MobileNet, Xception, Inception, and Inception ResNet v2 for the diagnosis of COVID-19. According to this study, VGG19 and MobileNet showed enhanced performance compared to the other models with an accuracy of 98.75% and 97.40%. Another comparative study was performed by Narin et al. (2021) on using ResNet50, ResNet152, ResNet101, Inception-ResNetV2 and InceptionV3 to diagnose COVID-19 from chest x-ray images of three different datasets. According to this study, it was observed that ResNet50 performed better than other models with the accuracies of 96.1%, 99.5%, and 99.7% on all the three datasets. Sethy and Behera (2020) diagnosed COVID-19 from x-ray images using a support vector machine trained with features extracted by the ResNet50 model. Song et al. (2021) developed a deep learning-based diagnosis system known as DeepPneumonia to diagnose COVID-19 and bacterial pneumonia. In this work, the authors used data collected from 86 healthy persons, 101 patients diagnosed with bacterial pneumonia, and 88 patients diagnosed with COVID-19. This data was collected from 19 hospitals in China. This model was tested with images from two datasets. Zheng et al. (2020) developed a weakly-supervised deep learning model for the diagnosis of COVID-19 from chest
### Table 16. ML and DL methods in Nephrology.

| Author                  | Method                      | Diagnosis/Application                  | Metric      | Findings   |
|-------------------------|-----------------------------|----------------------------------------|-------------|------------|
| Charleonnan et al. (2016) | Support Vector Machine      | Chronic kidney disease                 | Accuracy    | 98.3%      |
|                         |                             |                                        | Sensitivity | 99%        |
|                         |                             |                                        | Specificity | 98%        |
|                         | Logistic Regression         |                                        | Accuracy    | 96.55%     |
|                         |                             |                                        | Sensitivity | 94%        |
|                         |                             |                                        | Specificity | 98%        |
|                         | Decision Tree               |                                        | Accuracy    | 94.8%      |
|                         |                             |                                        | Sensitivity | 93%        |
|                         |                             |                                        | Specificity | 96%        |
|                         | K-Nearest Neighbour         |                                        | Accuracy    | 98.1%      |
| Chen et al. (2014)      | Support Vector Machine      | Chronic kidney disease                 | Accuracy    | 82%        |
| Wickramasinghe et al. (2017) | Multiclass Logistic Regression | Diet plan for chronic kidney disease | Accuracy    | 89.17%     |
|                         | Multiclass Neural Network   |                                        | Accuracy    | 82.50%     |
|                         | Multiclass Decision Forest  |                                        | Accuracy    | 99.17%     |
|                         | Multiclass Decision Jungle  |                                        | Accuracy    | 97.50%     |

### Table 17. ML and DL methods in Ophthalmology.

| Author                  | Method                      | Diagnosis/Application                  | Metric      | Findings   |
|-------------------------|-----------------------------|----------------------------------------|-------------|------------|
| Malik et al. (2019)     | Decision Tree               | Glaucoma, Unspecified primary angle-closure glaucoma | Accuracy    | 85.81%     |
|                         | Random Forest               |                                        | Accuracy    | 86.63%     |
|                         | Naive Bayes                 |                                        | Accuracy    | 81.53%     |
|                         | Neural Network              |                                        | Accuracy    | 85.98%     |
| Selvathi and Suganya (2019) | Support vector machine     | Diabetic eye disease                   | Accuracy    | 86.22%     |
|                         |                             |                                        | Sensitivity | 94.07%     |
|                         |                             |                                        | Specificity | 79.17%     |
| Santhakumar et al. (2016) | Support Vector machine      | Diabetic retinopathy                   | Accuracy    | 96%        |
|                         |                             |                                        | Sensitivity | 94%        |

### Table 18. ML and DL methods in Drug Discovery.

| Author                  | Method                      | Application                  | Metric      | Findings   |
|-------------------------|-----------------------------|-------------------------------|-------------|------------|
| Ongun et al. (2001b)    | SVM                         | Drug design                   | Error       | 0.1269     |
| Peter et al. (2012b)    | Random Forest               | Proximal tubular toxicity     | Sensitivity | 89.0%      |
|                         |                             |                                | Specificity | 85.0%      |
|                         |                             |                                | Accuracy    | 87.0%      |
| Khalaf et al. (2016b)   | Naive Bayesian Classifier   | Drug likeliness               | Accuracy    | 90.9%      |
|                         |                             |                                | Accuracy    | 91.4%      |
CT images. In this work, a pre-trained U-Net architecture is used to segment the lung region from the image and a 3D deep neural network was used to diagnose the COVID-19 infection in the lungs. This system is very fast at it takes only 1.93s to process a CT image of a patient and diagnoses the disease with an accuracy of 90.1% and specificity of 91.1%. Xue et al. [2020] proposed a methodology to diagnose COVID-19 pneumonia and Influenza-A viral pneumonia. In this methodology, a 3D CNN model is used to segment the candidate regions in the lungs and a location-attention classifier is used to classify these regions into COVID-19 pneumonia, influenza-A viral pneumonia and as normal and finally, a noisy or Bayesian function is used to calculate the infection probability. Barstugan et al. [2020] performed a study on using a support vector machine as a classifier trained with features extracted using five different algorithms for the diagnosis of COVID-19 CT images. The five feature extraction algorithms that were used in this work are Local Directional Pattern(LDP), Grey Level Co-occurrence Matrix(GLCM), Grey-Level Size Zone Matrix (GLSZM), Grey Level Run Length Matrix (GLRLM), and Discrete Wavelet Transform (DWT). According to this study support vector machine trained with features extracted using the GLSZM algorithm performed better than other feature extraction algorithms with an accuracy of 99.68%. Mahdy et al. [2020] proposed a methodology to diagnose COVID-19 using multi-level thresholding and a support vector machine. Chen et al. [2020] designed a deep learning model using transfer learning U-Net for the diagnosis of COVID-19. For this work, 46,096 anonymous CT images are collected from 106 patients admitted to Renmin hospital in Wuhan city were used, out of which 51 patients are diagnosed with COVID-19. Pandit and Banday [2020] proposed a transfer learning model by fine-tuning the pre-trained model VGG16 for the diagnosis of COVID-19. Puaschunder et al. [2020] compared two deep learning models that were built using the transfer learning of residual networks ResNet34 and ResNet50 for the diagnosis of pneumonia and COVID-19. According to this paper, ResNet50 performed better than ResNet32 with an accuracy of 72.38%. Shiby et al. [2020] proposed a deep learning model that is designed using VGG16 and a faster R-CNN framework to diagnose COVID-19.

4. Discussion

4.1. Smart Healthcare Systems using ML and DL

The usage of ML and DL models created a massive impact across all domains especially, the healthcare industry. Even with the advent of many reports and scans, human decision making is the only way for diagnosing diseases. This may sometimes lead to unreliable diagnosis due to bias in human decisions. Smart intelligent techniques like ML and DL methodologies can be used to improve reliability in diagnosis thereby saving lot of human lives. Thus researchers started proposing various models for automating diagnosis in healthcare in various specializations including Orthopedics (estimating bone density, diagnosing rheumatoid arthritis), Radiology (interpreting mammography, computed tomography and magnetic resonance imaging scans), Ophthalmology (diagnosis of diabetic retinopathy, cataract, glaucoma), Cardiology (diagnosis of complex diseases like hypertrophic cardiomyopathy) and many more. Such diagnosis may help saving lives of human. For eg., according to a study performed by the American Cancer Society Egan [1966] it was found that more than 50% of the women who are getting annual mammograms over 10 years are having false-positive findings. These false-positive findings in mammograms can lead to unnecessary examinations like ultrasound scans, MRI, and even biopsies and this can be avoided by using ML and DL based systems.

4.2. Impact of Computerized diagnostic systems on physicians

Machine learning and deep learning are playing a key role in all stages of drug discovery. These techniques are used extensively for better understanding of disease mechanisms, non-disease and disease phenotypes, to identify novel targets and in development of biomarkers for drug efficiency and prognosis. These systems are becoming more effective than medical professionals in terms of diagnosis and predictive analysis of diseases. Puaschunder [2020], Loh [2018]. This led to a major concern that these systems will replace medical professionals in near future, especially radiologists. The main reason for this concern is its ability to learn from millions of images and this learning enables the computer systems to diagnose the most complex diseases that are difficult to be diagnosed by experienced medical professionals. But there are few limitations with these systems, so we can’t completely depend on these systems for diagnosis. But these systems can be a part of a radiologist’s life, by assisting them during diagnosis and making their work more accurate and efficient.

In the case of other medical specialties, computer systems cannot be a replacement for doctors because these systems cannot gain trust in patients and cannot have high-level interactions with the patients. Even though one might say that there is a possibility that these systems can make clinical conversations in the future. But, even if computer systems are built to an extent that they can conduct real-time MRL CT, and other imaging examinations and perform automated surgeries, they cannot replace doctors. Doctors are still needed for the diagnosis and treatment of novel and ambiguous cases. These computer systems underperform in case of novel diseases, side effects caused by drugs because there is no prior instance available for these systems to learn from Froomkin et al. [2019]. For these reasons, it can be concluded the smart intelligent computer systems will support doctors by assisting them during the diagnosis and treatment of diseases instead of replacing them.

5. Conclusion

The diagnosis of diseases is a complex and time consuming process. The conventional procedures followed to diagnose diseases are not so accurate. Intelligent computer systems are being used by medical professionals for fast and accurate diagnosis of diseases. There is a lot of research that is done in this field. So the main aim of this paper is to present a comprehensive survey of different machine learning and deep learning models that
| Author                  | Method                                                                 | Disease                          | Metrics   | Findings  |
|------------------------|------------------------------------------------------------------------|----------------------------------|-----------|-----------|
| Hemdan et al. (2020)   | Ensemble of 7 convolutional neural networks                             | COVID-19                         | f1-score  | 0.91      |
| Wang et al. (2020)     | Deep CNN                                                              | Pneumonia and COVID-19           | Accuracy  | 92%       |
| Sethy and Behera (2020)| Support vector machine trained with features extracted by VGG16       | COVID-19                         | Accuracy  | 95.38%    |
| Song et al. (2021)     | Deep CNN                                                              | COVID-19 and bacterial pneumonia | Accuracy  | 86%       |
|                        |                                                                        |                                  | Sensitivity | 96%       |
| Xu and Meng            | Transfer learning of InceptionV3                                       | COVID-19 and viral pneumonia     | Accuracy  | 89.5%     |
| Zheng et al. (2020)    | U-Net based segmentation and weakly supervised learning based classifier | COVID-19                         | Accuracy  | 90.1%     |
| Xu et al. (2020)       | 3D CNN based segmentation with attention based classifier              | COVID-19 pneumonia and Influenza A viral Pneumonia | Accuracy | 86.7%     |
| Mahdy et al. (2020)    | Multi-level thresholding and SVM                                       | COVID-19                         | Accuracy  | 97.84%    |
|                        |                                                                        |                                  | Sensitivity | 95.76%    |
|                        |                                                                        |                                  | Specificity | 99.7%     |
| Chen et al. (2020)     | Transfer learning of U-Net                                             | COVID-19                         | Accuracy  | 98.85%    |
| Pandit and Banday (2020)| Transfer learning by fine tuning VGG16                                 | COVID-19                         | Accuracy  | 96%       |
| Shibly et al. (2020)   | CNN designed using VGG16 and Faster RCNN framework                    | COVID-19                         | Accuracy  | 97.36%    |
|                        |                                                                        |                                  | Sensitivity | 97.65%    |
|                        |                                                                        |                                  | Precision  | 99.28%    |
are developed and used in building computer systems to diagnose diseases across various specializations of medicine. Along with the survey, we discuss the advancements in healthcare with machine learning and deep learning-based systems and also the impacts of these systems on medical professionals. This paper provides a deep dive into the different frameworks, models and tools along with practical concerns and considerations in Health care domain that include Dental medicine, Haematology, Surgery, Cardiology, Pulmonology, Orthopaedics, Radiology, Oncology, General medicine, Psychiatry, Endocrinology, Neurology, Dermatology, Hepatology, Nephrology, and Ophthalmology. Along with the medical specializations mentioned above, we also present the survey of machine learning and deep learning models in drug discovery.

5.1. Highlights of the work

- Exploring prominent research works in designing the various robust Intelligent health care systems using ML and DL techniques for early diagnosis of diseases.

- Examining constructive research outputs demonstrating a promising supplementary diagnostic method for frontline clinical doctors and surgeons.

- Thorough analysis of applications of ML and DL across 16 medical specialties, namely Dental medicine, Haematology, Surgery, Cardiology, Pulmonology, Orthopaedics, Radiology, Oncology, General medicine, Psychiatry, Endocrinology, Neurology, Dermatology, Hepatology, Nephrology, Ophthalmology, and Drug discovery.

- Deep dive into the different ML and DL frameworks, models and tools along with practical concerns, challenges and considerations in Health care domain.

- Investigating the use of ML and DL mechanisms in predicting COVID-19, the deadly and infectious disease.

- Look into the impact of Computerized diagnostic systems on physicians with a promising discussion on future research deliberations.

- Recording relevant list of Public Data sets available for future works.

6. Suggestions for future work

- Fuzzy based diagnosis systems can be built to diagnose complex diseases like cancers, heart attacks, and diabetic retinopathy.

- Building Neural network-based systems to diagnose diseases from image-based data like X-rays, CT, and MRI scans.

- Transfer learning models can be built to diagnose diseases that are difficult to detect, like novel fevers, celiac disease, brain, and ovarian cancers, diabetic eye disease, and glaucoma.

- Designing systems with machine learning and Internet of Things(IoT) techniques for the evaluation of organs and for diagnosis of Haematological diseases from blood samples.

- Developing a pattern recognition based model for the diagnosis of Cardiovascular and Pulmonary diseases.

- Building hybrid systems with image recognition approaches for the staging of various cancers, for diagnosis of neurological diseases like brain hemorrhage and hydrocephalus.

- Developing robots and Surgeon-assisting tools with machine learning techniques to perform robotic and minimally invasive surgeries.

- Building a system that estimates the stress levels and suggests lifestyle changes that are needed to reduce stress.

- Building systems with a different combination of algorithms using ensemble methods for diagnosing diseases.

7. List of abbreviations

- AI - Artificial Intelligence
- ML - Machine learning
- DL - Deep learning
- MRI - Magnetic Resonance Imaging
- RVG - Radio Videography
- CNN - Convolutional Neural Network
- UCI - University of California
- MLP - Multi Layer Perceptron
- RBF - Radial Bias Function
- hiPCS - Human induced pluripotent stem cells
- TCMCD - Traditional Chinese medicine compound database
- ECG - Electrocardiogram
- ReLU - Rectified Linear Unit
- HCM - Hypertrophic cardiomyopathy
- SPET - Single-photon emission computed tomography
- MACE - major adverse cardiac events
- ARDS - Acute diseases like Respiratory distress syndrome
- ROC - Receiver operating characteristic
- EDR - Electrocardiogram derived respiratory
- CT - Computed tomography
- JSN - Joint space narrowing
- SWI - Susceptibility weighted imaging
- LASIK - Laser-Assisted In-Situ Keratomileusis
- IoT - Internet of Things
- SVM - Support Vector Machine
- KNN - K-Nearest Neighbor
- LMLA - Levenberg Marquardt Learning Algorithm
- DWNN - Distance-weighted -nearest-neighbor
- ELM - Extreme Learning Machine
- RVM - Relvence Vector Machine
- LVQ - Linear Vector Quantization
- LR - Logistic Regression
- GA - Genetic Algorithm
- GAN - Generative adversarial neural networks
8. List of public datasets

- ChestXpert  
  https://stanfordmlgroup.github.io/competitions/chexpert/

- ChestXray-NIHCC  
  https://nihcc.app.box.com/v/ChestXray-NIHCC

- MIMIC-CXR  
  https://physionet.org/physiobank/database/mimiccxr/

- PadChest  
  http://bimcv.cipf.es/bimcv-projects/padchest/

- IBM Xray Eye Gaze  
  https://physionet.org/content/egd-cxr/1.0.0/

- Cancer Image Archive  
  http://www.cancerimagingarchive.net

- National Lung Screening Trial  
  https://wiki.cancerimagingarchive.net/display/Public/LIDC-IDRI

- DeepLesion  
  https://nihcc.app.box.com/v/DeepLesion

- EchoNet-Dynamic  
  https://echonet.github.io/dynamic/

- ABCD Neurocognitive Prediction Challenge  
  https://sbris.rri.com/abcd-np-challenge/

- AAPM Sparse-View CT Reconstruction Challenge  
  https://www.aapm.org/GrandChallenge/ DL-sparse-view-CT/

- Cross-Sectional Multidomain Lexical Processing  
  https://openneuro.org/datasets/ds002236

- Neurite-OASIS  
  https://github.com/adalca/medical-datasets/blob/master/neurite-oasis.md

- MRNet  
  https://stanfordmlgroup.github.io/competitions/mrnet/

- fastMRI  
  https://fastmri.med.nyu.edu/

- OCMR  
  https://ocmr.info/

- PREVENT-AD  
  https://openpreventad.loris.ca/

- Medical Segmentation Decathlon  
  http://medicaldecathlon.com/

- MASSIVE  
  http://massive-data.org/download.html

- AOMIC: the Amsterdam Open MRI Collection  
  https://nilab-uva.github.io/AOMIC.github.io/

- MRdata  
  http://mridata.org/

- Brain MRI LGG FLAIR abnormality segmentation  
  https://www.kaggle.com/mateuszbuda/lgg-mri-segmentation

- Studyforrest  
  http://studyforrest.org/data.html

- Lung Image Database Consortium  
  https://wiki.cancerimagingarchive.net/display/Public/LIDC-IDRI

- UK Biobank  
  https://biobank.ctsu.ox.ac.uk/crystal/download.cgi

- BrixIA: COVID19 severity score assessment database  
  https://brixia.github.io/

- COVID-CT  
  https://github.com/UCSD-AI4H/COVID-CT

- Medical Imaging Data Resource Center (MIDRC)  
  https://wiki.cancerimagingarchive.net/pages/viewpage.action?pageId=70230281

- BIMCV-COVID19  
  http://bimcv.cipf.es/bimcv-projects/bimcv-covid19/

- MosMedData Covid19  
  https://mosmed.ai/en/

- COVID-19 LUNG CT LESION SEGMENTATION CHALLENGE  
  https://covid-segmentation.grand-challenge.org/Data/

- MedSeg COVID-19 CT  
  http://medicalsegmentation.com/covid19/

- COVID-Chest XRay  
  https://github.com/ieee8023/covid-chestxray-dataset

- BSI COVID19  
  https://bstitcov19.cimar.co.uk/worklist/?embedded=

- RICORD  
  https://www.rsna.org/covid-19/COVID-19-RICORD/ RICORD-resources

- FIRE (Fundus Image Registration Dataset)  
  https://paperswithcode.com/dataset/fire

- DRIVE: Digital Retinal Images for Vessel Extraction  
  https://drive.grand-challenge.org/

- FLARE: Fast and Low GPU memory Abdominal Organ Segmentation  
  https://flare.grand-challenge.org/

- Diabetes  
  https://archive.ics.uci.edu/ml/datasets/Diabetes

- Thyroid Disease  
  https://archive.ics.uci.edu/ml/datasets/Thyroid+Disease
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