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A COMPARISON OF CLASSICAL MACHINE LEARNING AND DEEP LEARNING METHODOLOGIES IN HEALTHCARE IMAGE CLASSIFICATION FOR VARIOUS DISEASES

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ABSTRACT: Deep learning and machine learning are increasingly being utilized to evaluate medical pictures and address machine intervention difficulties. While existing deep-learning and machine learning technologies are adaptive, they need medical image analysis-specific capabilities and need substantial research before they can be applied in this sector. Consequently, several research teams have built incompatible infrastructure and spent critical time repeating their work. This article offers several medical pictures for various conditions that may be used to use machine learning and deep learning approaches. Images of the heart, chest, lungs, musculoskeletal system, eye, breast, and skin are used for comparison. Comparisons between deep learning and machine learning for the same illnesses using various images and approaches are primarily studied, and the findings of the research are made available to the public so they can be utilized, improved, and developed upon.

Keywords- Deep learning, machine learning and medical images.

1. INTRODUCTION

Researchers developed automatic analysis techniques as soon as medical images could be processed and submitted. Medical image processing throughout the 1970s and 1990s included successively applying low-level imaging techniques (edge and line detection filters, region expansion) and mathematical modeling (fitting lines, circles, and ellipses) to solve specific issues. Expert systems that used if-then-else statements were standard in Intelligence at the time. In the late 1990s, medical image classification increasingly embraced supervised techniques, in which a machine-learning model is employed to build a system. Examples include active shape models (for segmentation), atlas techniques (fitted atlases using data for training), extraction and classification, and statistical classifiers (for computer-aided detection and diagnosis). This classification methodology, also known as machine learning, is still widely utilized in many computer-aided diagnostic categorization systems. As a result, we have seen a shift from human-designed to computer-trained systems that use example data to extract feature vectors. The optimal high-dimensional classification function is determined using computer algorithms. The extraction of image features is a critical stage in the design of such systems. This is still done by people; thus, specialized systems are utilized. Medical imaging is an important part of many clinical decisions and patient journeys. Computer-aided screenings, diagnosis, patient management, intervention, and therapy all make use of medical images. Medical imaging remains an important aspect of many clinical tasks. Still, a scarcity of qualified radiologists to interpret complex images highlights the need for trustworthy automated solutions to alleviate the increasing load on healthcare practitioners. Because of the competence and prior knowledge required to deal with so much data, there is usually significant inter- and inter-observation variation in categorizing medical data. As a result, there is disagreement on what constitutes a gold-standard testing dataset annotation. Because we require several expert datasets (oracles) to reach an agreement, these problems raise the cost of labeling and re-labeled medical picture datasets. Researchers in medical image analysis are using DL (Deep Learning) and ML (Machine Learning) algorithms for various applications, and the results are encouraging. The use of DL and ML in medical imaging recently received a lot of attention.

Medical imaging, such as CT, MR, PET, mammography, ultrasound, X-ray, and others, has been more significant for early sickness diagnosis, detection, and treatment in recent decades. Technologists and physicians in the medical field examine medical pictures. Researchers and doctors are increasingly embracing computer-assisted therapy due to disease unpredictability and expert fatigue. Machine learning, as well as deep learning technologies, have recently enhanced computerized medical image analysis, which was late. Optimized feature extraction or representations is critical to machine learning's efficacy. Relevant or task-related qualities were typically developed by human architecture and were influenced by their grasp of targeted domains, making machine learning approaches challenging for nonexperts to implement. Deep learning has addressed these obstacles by using feature engineering throughout training. Deep learning, rather than hand-designing features, requires a gathering of data with little pre-processing and then self-teaching relevant interpretations. Because feature engineering is now performed by a machine, non-experts in computer vision may use machine learning and deep learning to conduct their own research and/or implementations, notably medical picture analytics.

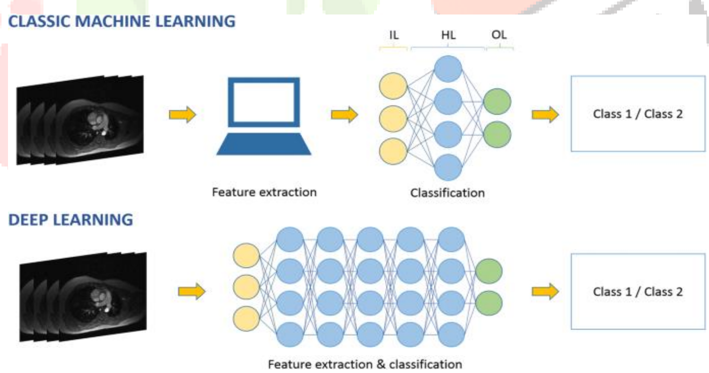


Fig 1. classic machine learning and deep learning

2. MACHINE LEARNING

Machine learning (ML) is a subset of artificial intelligence (AI) that allows computers to autonomously learn from data and prior experiences while simultaneously detecting patterns to make predictions with little human input. Machine learning methods enable computers to perform autonomously without the requirement for explicit programming. Machine learning applications are regularly updated with new data, allowing them to automatically learn, develop, expand, and adapt. Machine learning can extract usable information from huge volumes of data by using algorithms that recognize patterns and learn from previous experiences in an iterative process. Instead of relying on any predetermined equation that may serve as a model, algorithms for machine learning use computational methods to learn directly from data. This contrasts with traditional methods. The effectiveness of machine learning algorithms will dynamically improve with an increase in the number of samples they have access to throughout the 'learning' processes. For example, one of the subfields of machine learning is called "deep learning," and it trains computers to mimic natural human behaviors such as studying from examples. It gives performance parameters that outperform typical ML algorithms. Although the notion of learning algorithms is not new – it goes back to the Second World War and the deployment of the Enigma Code – the capacity to apply complex mathematical calculations organically to rising urbanization and differences in data available is a recent development.

Today, because of the advent of big data, IoT (Internet of Things), and cognitive computing, machine learning is becoming indispensable for tackling challenges in several fields, including the ones listed below.

- Finance via computation (credit scoring, algorithmic trading)
- Vision in computers (facial recognition, motion tracking, object detection)
- Computational biology (DNA sequencing, detection of brain tumors, drug development)
- Manufacturing, automotive, and aerospace (predictive maintenance)
- Natural language understanding (voice recognition)

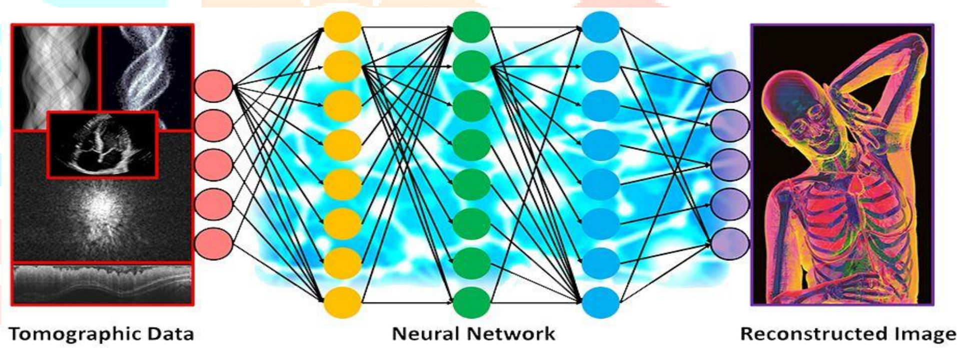


FIG 2. Machine Learning in medical images

3. DEEP LEARNING

Deep learning is a branch of artificial intelligence and machine learning (AI) that aims to replicate how individuals learn specific aspects of information. Deep learning is a critical component of the subject of data science, which also includes statistics and predictive modeling. Deep learning makes the process of acquiring, analyzing, and interpreting massive amounts of data faster and easier, which is beneficial to scientists who are tasked with carrying out these tasks.

Deep learning may be thought of as a method for automating predictive analytics at its most basic level. In comparison to the linear arrangement of standard machine learning algorithms, deep learning algorithms are layered in a hierarchy of organizing several complicated and abstraction.

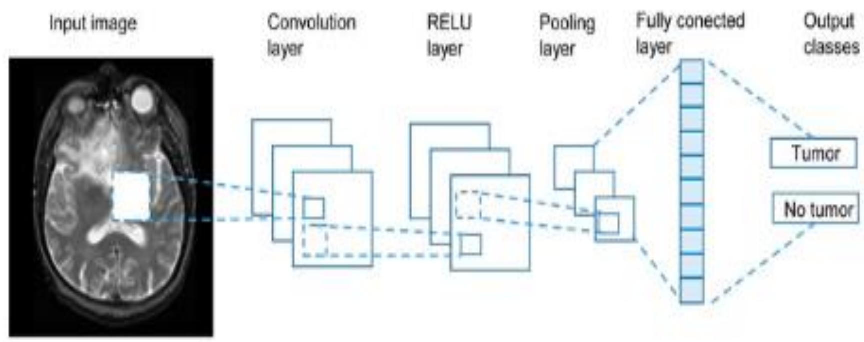


FIG 3. DEEP LEARNING IN MEDICAL IMAGES

4. IMPLEMENTATION OF ML AND DL METHODS FOR VARIOUS DISEASES WITH DIFFERENT IMAGES

4.1. ML AND DL FOR BRAIN IMAGES (MULTIPLE MRI IMAGES) BRAIN TUMOR

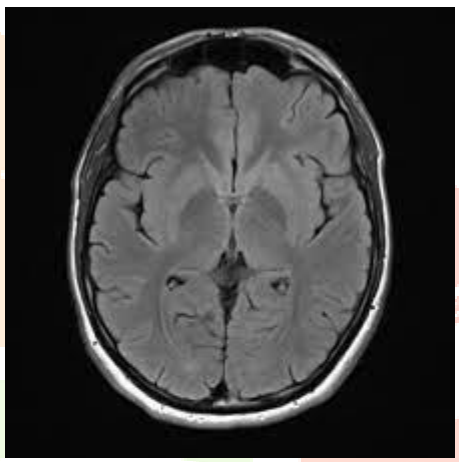


FIG 4. MRI BRAIN IMAGES

The MRI of the brain is examined a total of ten times to create the imaging data set. The images are trained and examined using machine learning methods, and then the accuracy of the image is assessed using an SVM classifier. The graph then displays the average of the 10 MRI images. The graph provides the most accurate representation of the overall accuracy. The findings indicate that ML is liable for achieving an accuracy of 67%.

A total of ten different brain MRI scans are used to compile an image data collection. The pictures are trained and evaluated using deep learning methods, and then the accuracy of the images is assessed by a CNN (Convolutional Neural Networks) classifier. The graph then displays the average of the 10 MRI images. The graph provides the most accurate representation of the overall accuracy. According to the findings, DL is responsible for producing an accuracy of 71.2%.

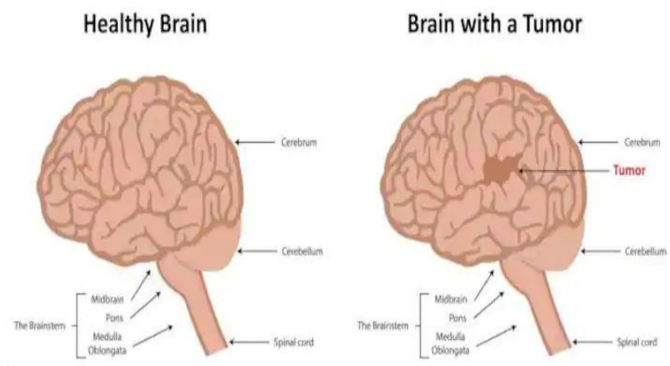


FIG 4.1 NORMAL AND TUMOR BRAIN

4.2. ML AND DL FOR CARDIAC IMAGES (CMR IMAGES) DILATED CARDIOMYOPATHY

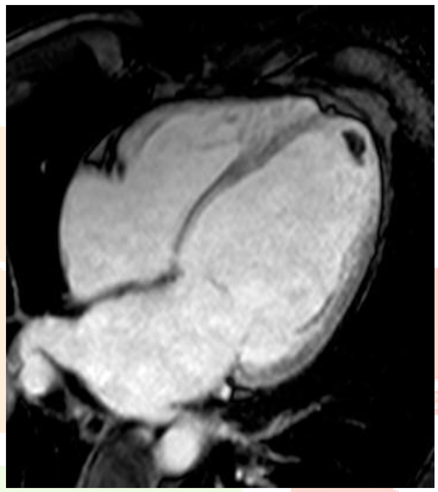


FIG 5. CARDIAC CMR IMAGES

Machine learning (ML) is transforming CMR in several ways. This focuses on how machine learning may enhance the speed, quality, and analysis of CMR imaging. CMR segmentation and analysis times have been lowered because of machine learning. Commercially available instruments can correctly and consistently assess left and right ventricular mass and volume. Reducing image capture and reconstruction time, enhancing the spatial and temporal resolution, and analyzing the open-source publication of computational processes and datasets reduce the danger of ML technique failure.

A total of 10 CMR images of the CARDIAC are performed to generate the scanning data set. An SVM classifier is then used to evaluate the image's accuracy after it has been developed and inspected using machine learning techniques. The average of the 10 CMR pictures is then shown on the graph. The graph gives the most precise illustration of the overall precision. The results reveal that ML is accountable for reaching 70% accuracy.

Ten distinct CMR CARDIAC IMAGES are used to construct an image data collection. A CNN (Convolutional Neural Networks) classifier determines the accuracy of the images after they have been trained and evaluated using deep learning techniques. The average of the 10 CMR pictures is then shown on the graph. The graph gives the most precise illustration of the overall precision. According to the data, DL is accountable for 83 percent of the accuracy.

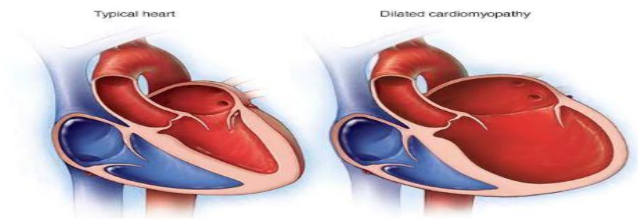


FIG 5.1 NORMAL AND DILATED HEART

4.3 ML AND DL FOR CHEST IMAGES (X-RAY) PNEUMONIA

FIG 6. CHEST X-RAY IMAGES

To generate the imaging data set, the X-RAY of the chest is investigated ten times. Machine learning techniques are used to train and analyze the photos, and the correctness of the images is tested using an SVM classifier. The graph then shows the average of the ten X-RAY pictures. The graph represents the total accuracy the most accurately. According to the data, ML can obtain an accuracy of 70%.

To create an image data collection, 10 distinct chest X-RAY images are utilized. Deep learning techniques are used to train and analyze the photos, and the correctness of the images is measured by a CNN (Convolutional Neural Networks) classifier. The graph then shows the average of the ten X-RAY pictures. The graph represents the total accuracy the most accurately. According to the data, DL is accountable for 75% accuracy.

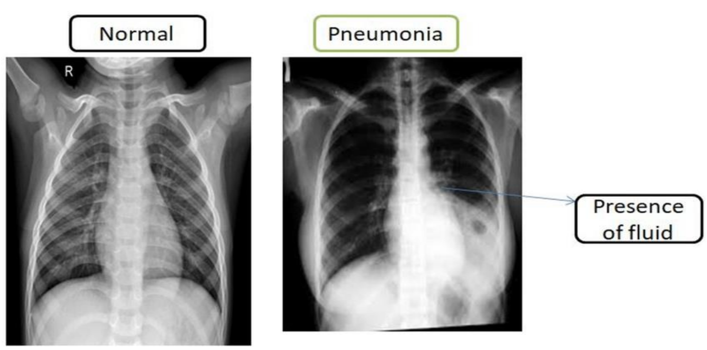


FIG 6.1 NORMAL AND PNEUMONIA CHEST

4.4 ML AND DL FOR LUNG IMAGES (CT) LUNG CANCER

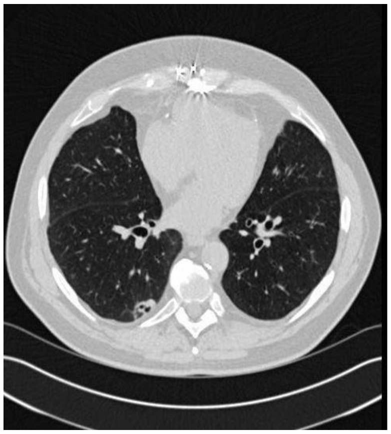


FIG 7. LUNG CT IMAGES

To compile the imaging data set, 10 different lung CT scan pictures are analyzed. Machine learning techniques are used to train and analyze the pictures, and an SVM classifier is then used to evaluate the images' correctness. After then, a graph showing an average of all 10 CT scans is shown. When it comes to graphically depicting the overall precision, the graph wins without trouble. According to the results, ML is to blame for a 77% success rate.

Ten unique CT scans of the lungs are utilized to generate the data set. A CNN (Convolutional Neural Networks) classifier is taught and tested using deep learning techniques to determine how accurate the pictures are. The aggregate of the 10 CT scans is then shown on a graph. The graph is the most reliable illustration of the whole reliability picture. The results indicate that 75% accuracy may be attributed to DL.

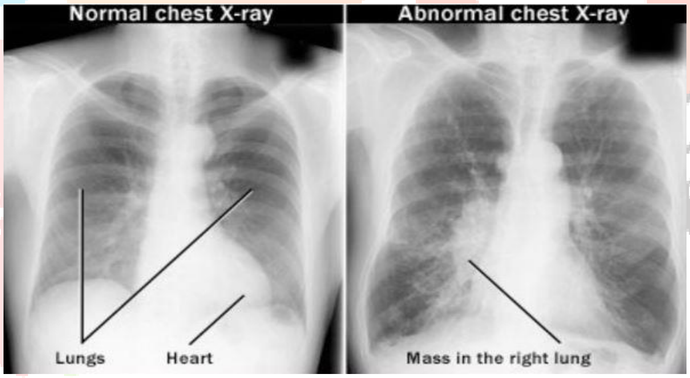


FIG 7.1 NORMAL AND CANCER LUNG

4.5 ML AND DL FOR MUSCULO-SKELETAL IMAGES (X-RAY)

FIG 8. MUSCULO-SKELETAL IMAGES (X-RAY) OF WRIST

To construct the imaging data set, the MUSCULOSKELETAL IMAGES of 10 images are evaluated. Machine learning techniques are used to train and analyze the photos, and the correctness of the images is tested using an SVM classifier. The average of the ten MUSCULOSKELETAL IMAGES is then shown on the graph. The graph represents the total accuracy the most accurately. According to the data, ML can obtain an accuracy of 70 %.

An image data collection is made up of 10 separate MUSCULOSKELETAL IMAGES. Deep learning techniques are used to train and analyze the photos, and the correctness of the images is measured by a CNN (Convolutional Neural Networks) classifier. The average of the ten MUSCULOSKELETAL IMAGES is then shown on the graph. The graph represents the total accuracy the most accurately. According to the data, DL is accountable for 82% accuracy.

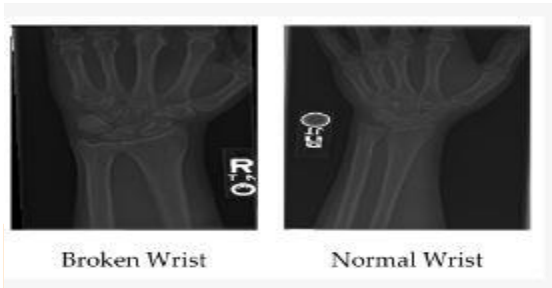


FIG 8.1 NORMAL AND BROKEN WRIST

4.6 ML AND DL FOR EYE IMAGES (Electroretinogram ERG IMAGE) RETINO BLASTOMA

FIG 9. EYE IMAGES (ELECTRORETINOGRAM ERG IMAGE)

For creating the imaging data set, 10 different versions of the ERG EYE IMAGE are analyzed. Machine learning techniques are used to train and analyze the pictures, and an SVM classifier is then used to evaluate the images' correctness. Next, the average of all 10 ERG EYE IMAGES is shown on the graph. The graph is the most reliable illustration of the whole reliability picture. According to the results, ML is to blame for a 62% success rate.

Ten distinct ERG EYE IMAGES are utilized to generate the data set. A CNN (Convolutional Neural Networks) classifier is taught and tested using deep learning techniques to determine how accurate the pictures are. Finally, the graph shows the average of all 10 ERG EYE IMAGES. The graph is the most reliable illustration of the whole reliability picture. This study found that DL was responsible for a 65% success rate.

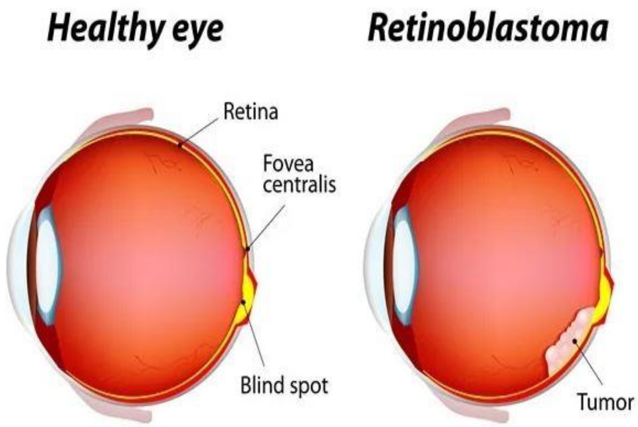


FIG 9.1 NORMAL AND TUMOR EYE

4.7 ML AND DL FOR BREAST IMAGES (MAMMOGRAPHY IMAGE) BREAST CANCER

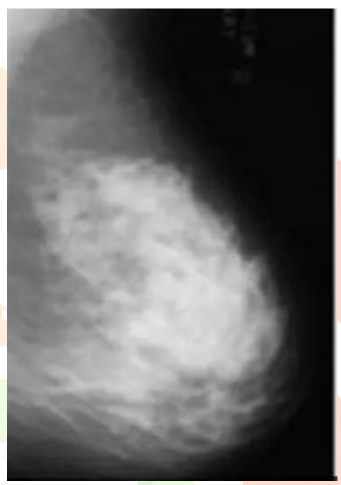


FIG 10. BREAST IMAGES (MAMMOGRAPHY IMAGE)

The imaging data set is made by looking at ten images of the MAMMOGRAPHY IMAGE. Machine learning is used to train and look at the images, and then an SVM classifier is used to judge how accurate the image is. The average of the 10 MAMMOGRAPHY IMAGE is then shown on the graph. The graph is the best way to show how accurate the whole thing is. The results show that ML is responsible for an accuracy of 81%.

Ten different MAMMOGRAPHY IMAGE are used to put together a set of image data. Deep learning is used to train and evaluate the images, and then a CNN (Convolutional Neural Networks) classifier checks the accuracy of the images. The average of the 10 MAMMOGRAPHY IMAGE is then shown on the graph. The graph is the best way to show how accurate the whole thing is. The results showed that DL was responsible for 89% of the accuracy.

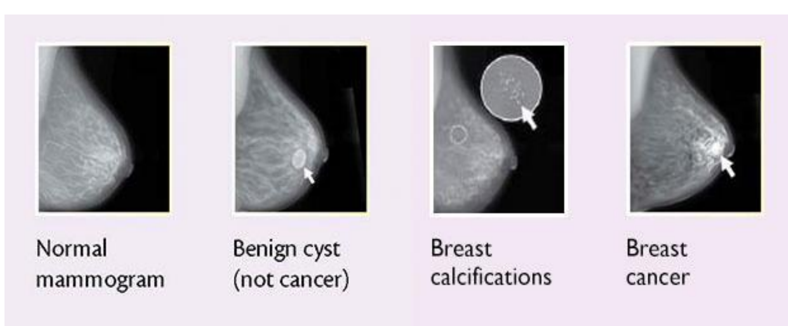


FIG 10.1 NORMAL AND CANCER BREAST IMAGE

4.8 ML AND DL FOR SKIN IMAGES (DERMOSCOPIC IMAGE) SKIN CANCER

FIG 11. SKIN IMAGES (DERMOSCOPIC IMAGE)

To construct the imaging data set, the DERMOSCOPIC IMAGE of is viewed 10 times. Machine learning techniques are used to train and analyze the photos, and the correctness of the images is tested using an SVM classifier. The graph then shows the average of the ten DERMOSCOPIC IMAGES. The graph represents the total accuracy the most accurately. According to the data, ML can obtain an accuracy of 71%.

To create an image data collection, 10 distinct DERMOSCOPIC IMAGES are employed. Deep learning techniques are used to train and analyze the photos, and the correctness of the images is measured by a CNN (Convolutional Neural Networks) classifier. The graph then depicts the average of the ten DERMOSCOPIC IMAGES. The graph represents the total accuracy the most accurately. According to the data, DL is accountable for 74% accuracy.

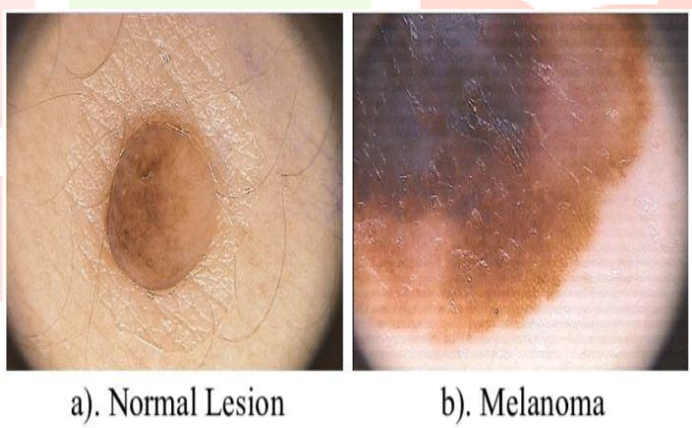


FIG 11.1 NORMAL AND CANCER SKIN

5. RESULTS AND DISCUSSION

In this study, we used several types of diseases with distinct types of images such as MRI, X-RAY, CT, ERG, MAMMOGRAPHY, and Dermoscopy images and trained with machine learning methods such as SVM. The images are retrieved and then image preprocessing is done with a median filter, and then SVM is used to classify the image into 2 classes by testing and training 10 images for every disease.

The deep learning strategy is used for the same photos, the images are tested and trained using CNN techniques, and the results are acquired and quantified using the accuracy rate.

When we compare ML (SVM) with DL (CNN), the accuracy of each illness is considered. Furthermore, deep learning methodologies outperform machine learning approaches in terms of accuracy. The final findings demonstrate that deep learning is the best method of image classification, and machine learning is occasionally employed. Deep learning algorithms may be employed with a larger number of data sets implemented. When fewer data sets are utilized, machine learning approaches perform better.

ALGORITHM :1

Pseudo-code of SVM Algorithm

Input: determine the various TESTING AND TRAINING image data.

Output: determine the calculated ACCURACY of the data set.

Select the **optimal** values for SVM.

WHILE (stopping condition is not met) **DO**

Implement SVM train step for each data point.

Implement SVM classify for testing data points.

END WHILE

RETURN *accuracy*

ALGORITH: 2

Pseudo-code for CNN algorithm

INPUT : medical image data

OUTPUT: integrity status

For each response of the image

Check the accuracy value

If(result)== empty or incorrect then

Integrity == false

Else

Integrity == true

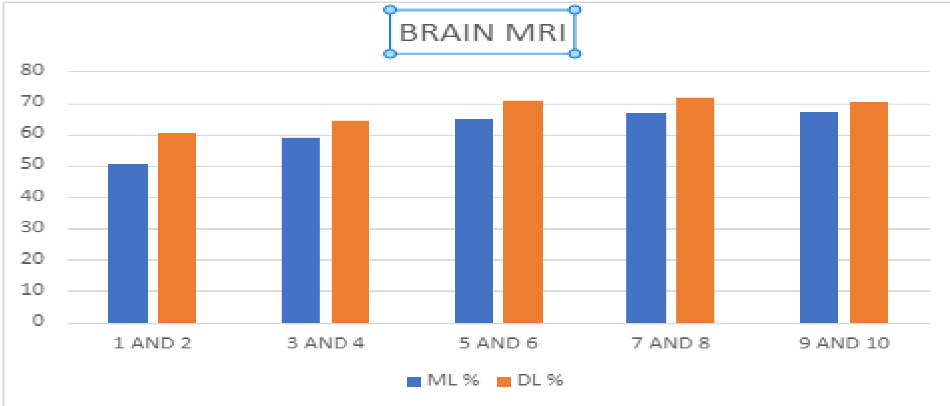
End if

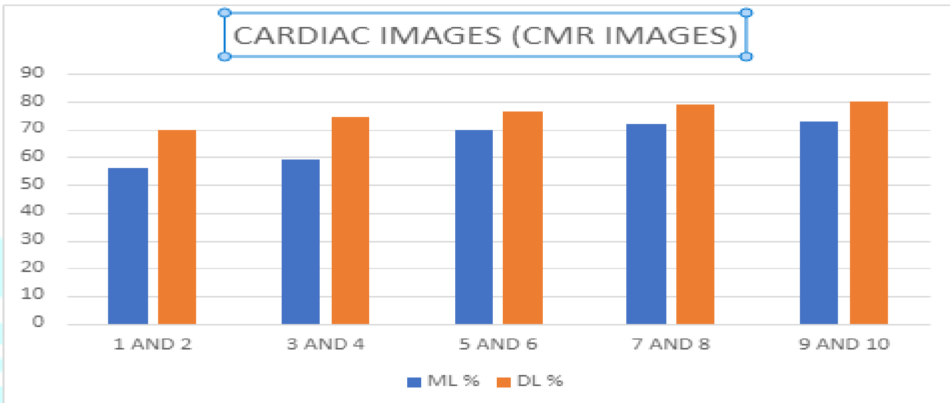
End for

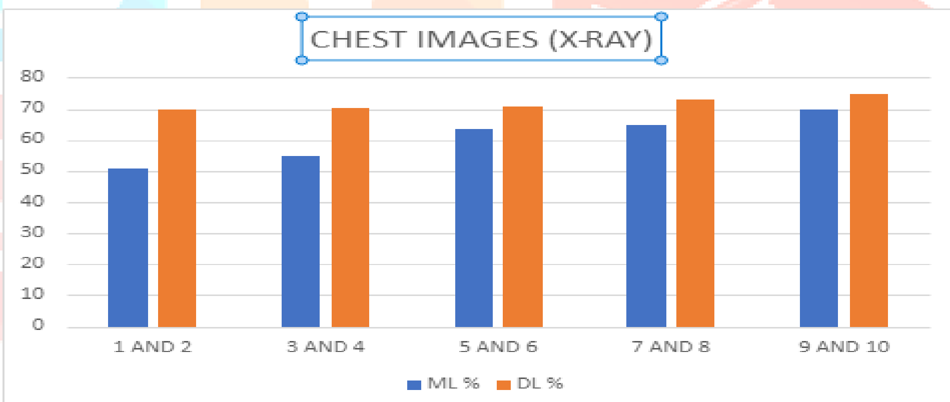
Return status

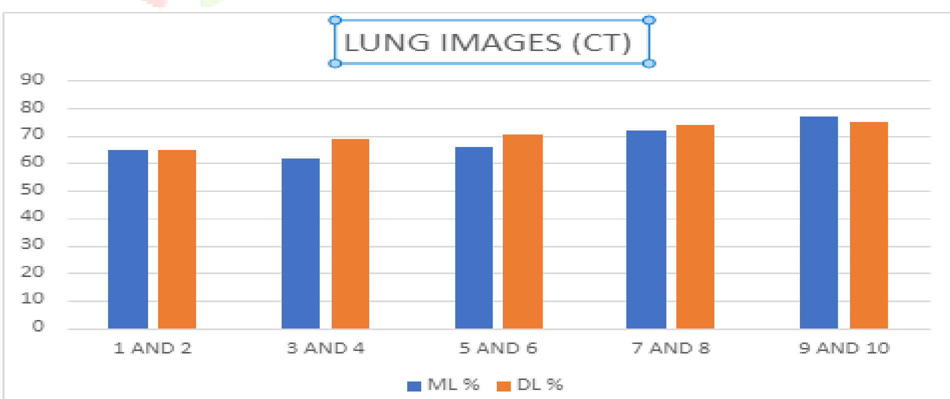
End

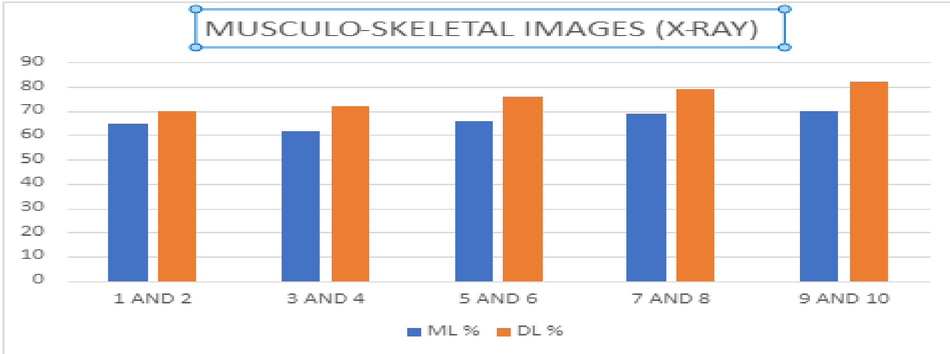
5.1 Representation of accuracy of each image in bar chart is shown in %.

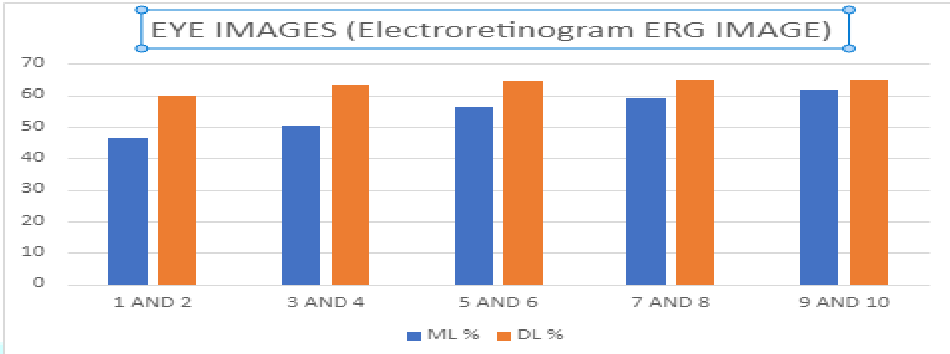


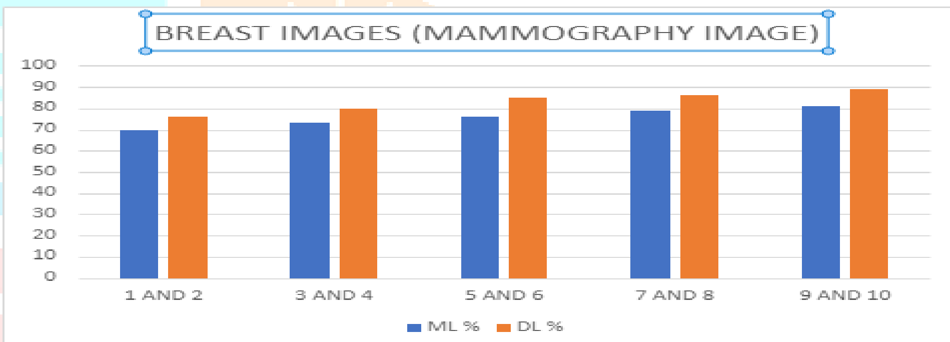


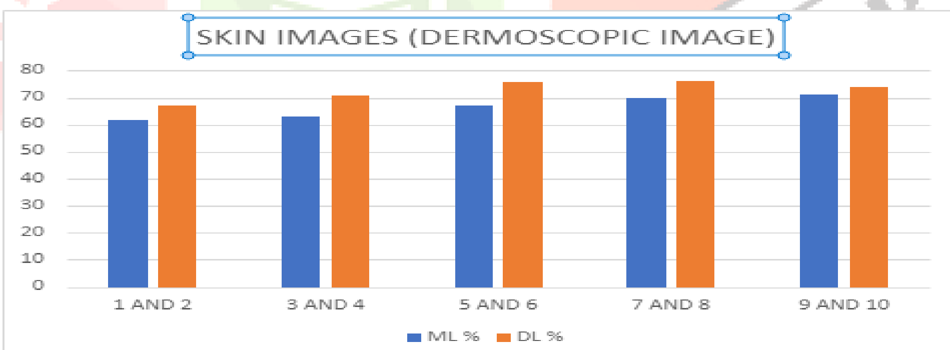












6. CONCLUSION

In this work, we employed MRI, X-RAY, CT, ERG, MAMMOGRAPHY, and Dermoscopy images and trained using SVM. SVM is used to classify the images into two classifications by testing and training 10 images for each disease. The same images are examined and trained using CNN technologies, and the outcomes are measured by accuracy. ML (SVM) and DL (CNN) accuracy are compared. Deep learning outperforms machine learning in accuracy. Deep learning is the best image classifying approach, although machine learning is used occasionally. Deep learning algorithms may use more data. Less data improves machine learning.

REFERENCES

[1]. Hwang, E. J. et al. Development and validation of a deep learning-based automated detection algorithm for major thoracic diseases on chest radiographs. JAMA Netw. Open 2, e191095. https://doi.org/10.1001/jamanetworkopen.2019.1095 (2019).

[2]. Gulshan, V. et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA 316, 2402–2410. https://doi.org/10.1001/jama.2016.17216 (2016).

[3]. Esteva, A. et al. Dermatologist-level classifcation of skin cancer with deep neural networks. Nature 542, 115–118. https://doi. org/10.1038/nature21056 (2017).

[4]. Ha, R. et al. Predicting breast cancer molecular subtype with MRI dataset utilizing convolutional neural network algorithm. J. Digit. Imaging 32, 276–282. https://doi.org/10.1007/s10278-019-00179-2 (2019).

[5]. Park, E. K. et al. Machine learning spproaches to radiogenomics of breast cancer using low-dose perfusion computed tomography: predicting prognostic biomarkers and molecular subtypes. Sci. Rep. https://doi.org/10.1038/s41598-019-54371-z (2019).

[6]. Guo, Y., Graber, A., McBurney, R. N. & Balasubramanian, R. Sample size and statistical power considerations in high-dimensionality data settings: a comparative study of classifcation algorithms. BMC Bioinform. 11, 447. https://doi.org/10.1186/1471-2105- 11-447 (2010).

[7]. Tan, X. et al. Wireless sensor networks intrusion detection based on SMOTE and the random forest algorithm. Sensors (Basel) https://doi.org/10.3390/s19010203 (2019).

[8]. Dhungel N, Carneiro G, Bradley AP. 2016. The automated learning of deep features for breast mass classification from mammograms. In: Conference on medical image.

[9]. Dhungel N, Carneiro G, Bradley AP. 2017a. Combining deep learning and convolutional neural networks for medical image computing. 225–240 DOI 10.1007/978-3-319-42999-1.

[10]. Dhungel N, Carneiro G, Bradley AP. 2017b. A deep learning approach for the analysis of masses in mammograms with minimal user intervention. Medical Image Analysis 37:114–128 DOI 10.1016/j.media.2017.01.009.

[11]. Kim, Y.-G., Lee, S.M., Lee, K.H., Jang, R., Seo, J.B., Kim, N., 2020. Optimal matrix size of chest radiographs for computer-aided detection on lung nodule or mass with deep learning. European Radiology 30 (9), 4943–4951. doi:10.1007/ s00330-020-06892-9.

[12]. Kitahara, Y., Tanaka, R., Roth, H., Oda, H., Mori, K., Kasahara, K., Matsumoto, I., 2019. Lung segmentation based on a deep learning approach for dynamic chest radiography. In: Medical Imaging 2019: Computer-Aided Diagnosis. SPIE, p. 130. doi:10.1117/12.2512711.

[12]. Kitamura, G., Deible, C., 2020. Retraining an open-source pneumothorax detecting machine learning algorithm for improved performance to medical images. Clin. Imaging 61, 15–19. doi:10.1016/j.clinimag.2020.01.008.

[13]. Johns Hopkins Coronavirus Resource Center. https://coronavirus.jhu.edu/ map.html. Accessed 14 Sep 2020

[14]. Huang C, Wang Y, Li X et al (2020) Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. Lancet 395:497–506. https://doi. org/10.1016/S0140-6736(20)30183-5

[15]. Clinical management of severe acute respiratory infection when COVID-19 is suspected. https://www.who.int/publications-detail/clinical-managementof-severe-acute-respiratory-infection-when-novel-coronavirus-(ncov)- infection-is-suspected. Accessed 13 Sep 2020.

[16]. Zhang, X., Sugano, Y., Fritz, M., and Bulling, A. (2017). It's Written All Over Your Face: Full-Face Appearance-Based Gaze Estimation. 51–60. Available online at: https://openaccess.thecvf.com/content_cvpr_2017_workshops/w41/ html/Bulling_Its_Written_All_CVPR_2017_paper.html (accessed November 4, 2020).

[17]. Zhang, X., Sugano, Y., Fritz, M., and Bulling, A. (2019). MPIIGaze: real-world dataset and deep appearance-based gaze estimation. IEEE Trans. Pattern Anal. Mach. Intell. 41, 162–175. doi: 10.1109/TPAMI.2017.2778103

[18]. Wang, W.; Li, X.; Yang, J.; Lu, T. Mixed Link Networks. IJCAI Int. Jt. Conf. Artif. Intell. 2018, 2819–2825, arXiv:1802.01808.

[19]. Redmon, J.; Farhadi, A. YOLOv3: An Incremental Improvement. CoRR 2018. Available online: http: //xxx.lanl.gov/abs/1804.02767 (accessed on 7 January 2020)

[20]. Liao H, Luo J. 2017. A deep multi-task learning approach to skin lesion classification. In: Joint Workshop on Health Intelligence W3PHIAI 2017 (W3PHI & HIAI), San Francisco, CA.

[21]. Lopez A, Giro-i Nieto X, Burdick J, Marques O. 2017. Skin lesion classification from dermoscopic images using deep learning techniques. In: 2017 13th IASTED International Conference on Biomedical Engineering, Innsbruck, Austria. 49–54.