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Digitization, Analysis & Prediction of Medical Reports Using Deep Learning

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***Abstract* — Advancements in Deep Learning have enabled the healthcare industry to efficiently process and analyze a vast amount of medical data, including critical information about patients' health. Medical reports, in particular, contain valuable data that can help identify trends, patterns, and anomalies in patients' medical conditions, leading to better diagnosis and treatment plans. In this paper, we present an approach that utilizes deep learning algorithms, specifically CNN to predict, digitize, and analyze medical reports. An approach is proposed that uses OCR technology to digitize the reports, making it easier to analyze and store them in a digital format. This approach has the potential to improve the accuracy, efficiency, and quality of medical diagnosis and treatment, and can address challenges such as doctor prescription digitization, brain tumor classification, kidney stone classification, and skin disease classification. The approach is implemented in an Android application built using React Native, which enables healthcare providers to access these services through their smartphones.**

Keywords—Medical Reports, Medical Services, Medical Reports Analysis, Human Diseases, Deep Learning, Prescription Digitization

I. INTRODUCTION

The healthcare industry has experienced a tremendous transformation with the emergence of digital technology. One such area where technology has shown remarkable progress is the prediction, digitization, and analysis of medical reports using deep learning techniques. Deep learning algorithms have proved to be incredibly useful in analyzing large volumes of medical data, identifying patterns, and making predictions.

Medical reports are crucial in diagnosing and treating patients, but their analysis can be time-consuming and error-prone when done manually. With the help of deep learning, medical reports can be digitized, allowing for easier access and analysis. Deep learning algorithms can analyze medical reports to identify patterns, such as symptoms, diseases, or other health issues, which can help medical professionals make more accurate diagnoses.

Moreover, deep learning can also be used to predict potential health issues in patients based on their medical history and other related factors. This can help doctors take proactive measures to prevent the onset of diseases and improve the overall health of patients. The potential benefits of this technology are enormous, including improved patient outcomes, reduced medical errors, and increased efficiency in healthcare delivery.

The utilization of digitized medical reports holds the potential for substantial cost savings in healthcare. Illegible handwriting in medical prescriptions has long been a concern, posing serious risks to patients, such as inaccurate dosages or incorrect medication being prescribed. A recent study [1] conducted an analysis of medication error reports from a national error reporting database, highlighting that nearly 88% of these errors could have been prevented.

Brain tumor is an abnormal growth of cells in the brain that can be cancerous or noncancerous. It can cause increased pressure inside the skull, which can lead to brain damage and be life-threatening. Deep learning technologies for brain tumor identification have the potential to revolutionize current approaches to diagnosis and treatment, improving the standard of care given to patients [3].

Kidney stones are a common urological issue that affect one in ten people globally [4]. The use of deep learning algorithms has become a promising approach in detecting kidney stones, offering an automated and efficient diagnosis of this condition. By identifying patterns in CT images, deep learning models can accurately and cost-effectively identify kidney stones.

Our methods leverage deep learning techniques to predict and classify medical conditions accurately and medical report digitization enhances the efficiency and effectiveness of healthcare services, enabling healthcare providers to make data-driven decisions that benefit patients' overall health outcomes.

II. LITERATURE REVIEW

The individual writing style of every person can make it difficult to read their handwriting, and this is particularly true for doctors who are often known for their illegible writing [6, 7]. Unfortunately, studies have shown that poor handwriting by doctors can lead to medical errors [8, 9]. One reason for this is the limited time doctors have to talk to each patient, which can cause them to rush when writing prescriptions. Additionally, some medicine names and abbreviations can look alike, and if written poorly, can be confusing for the reader [6].

Recognition systems play a crucial role in categorizing input patterns into the corresponding entities, although entities may vary depending on the system. Character recognition systems are responsible for classifying characters, and they are differentiated by the type of characters they recognize, whether they are printed, typewritten, or handwritten [10]. Recognizing a single character is relatively easy, but when it comes to cursive or

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mixed cursive words, recognition becomes challenging due to the unique writing styles, shapes, and sizes of the letters, which can make recognizing characters complex [11]. Character recognition is an essential field in image processing and pattern recognition. Its primary goal is to convert readable characters into a machine-readable format, such as ASCII or UNICODE, so that the text in an image can be converted into machine-readable text [12].

Personal Health Records (PHRs) have become increasingly popular in recent years, as they allow patients to access and manage their health information. According to healthit.gov [13], PHRs can help patients better manage their care by providing important health information such as immunization records, lab results, and medication lists. A study by Kim et al.[14] found that PHRs can improve patient engagement and satisfaction, as well as facilitate communication between patients and healthcare providers.

Researchers have developed different CNN architectures to detect brain tumors without the need for hand-crafted feature extractors or segmentation techniques. One example is a 16-layer CNN model proposed [15] by Sultan et al., achieving high prediction accuracies of 96.1% and 98.7% on datasets with 3064 and 516 images, respectively. Another study [16] by Hossain et al. utilized the Fuzzy C-Means clustering technique to extract tumor areas from MRI images and proposed a new CNN-based model. This model achieved a prediction accuracy of 97.9% and outperformed prior machine learning models.

Recent research has shown that deep learning algorithms can accurately detect and diagnose kidney stones. Studies by Caglayan et al.[17] and Zhang et al.[18] demonstrate the effectiveness of deep learning models in detecting kidney stones on computed tomography (CT) images and unenhanced CT images, respectively. These models have achieved high diagnostic accuracy rates, making them reliable tools for detecting kidney stones. Additionally, deep learning algorithms have shown potential in improving the accuracy and efficiency of brain tumor detection and classification, as demonstrated in experiments on publicly available brain MRI datasets.

III. PROPOSED METHODOLOGY

A. *Abbreviations and Acronyms*

CNN - Convolutional Neural Network
CT - Computed Tomography
DL - Deep Learning
MRI - Magnetic Resonance Imaging
PHR - Personal Health Record
OCR - Optical Character Recognition
VGG - Visual Geometry Group

B. *Prescription Digitization*

Digitizing prescriptions is a crucial step in modernizing healthcare systems. However, accurately recognizing and extracting information from handwritten prescriptions remains a significant hurdle. Traditional methods often struggle with the diversity of handwriting styles and the complexity of medical terminologies. Handwritten prescriptions present challenges due to the variability in handwriting styles, illegible text, and complex medical terminologies.

This research paper introduces an approach to address the challenges associated with recognizing handwritten prescriptions during the digitization process. The proposed method utilizes the Google Vision API for text extraction and OpenAI's ChatGPT for generating JSON data of the prescription. This innovative approach revolutionizes medical prescription management by combining the OCR technology of the Google Vision API with the advanced NLP capabilities of ChatGPT, facilitating the efficient conversion of prescription data into structured JSON format.

Methodology

The methodology depicted in Fig.1 provides an overview of the Prescription Digitization.

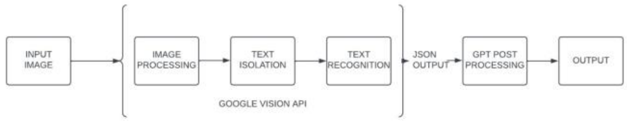

Fig. 1. Block Diagram of Prescription Digitization

The process begins by passing the prescription image or scanned document through the Google Vision API, which utilizes machine learning models to accurately extract text from the prescription. Vision API's advanced algorithms interpret and recognize the textual content, including details about the hospital or clinic, doctors, patients, tests, and the prescribed medications. This automated text extraction eliminates the need for manual transcription and significantly reduces the potential for human error.

To visualize the detected text, bounding boxes are drawn around each annotation. The coordinates of the bounding box vertices are obtained from the **`bounding_poly.vertices`** property of each text annotation. These vertices represent the corners of the rectangle surrounding the text. Using OpenCV's **`cv2.rectangle`** function, green rectangles are drawn around the detected text. The resulting image with the text annotations can be saved to a specified output path. This annotated image provides a visual representation of the detected text within the original image or document, as shown in Fig.2.

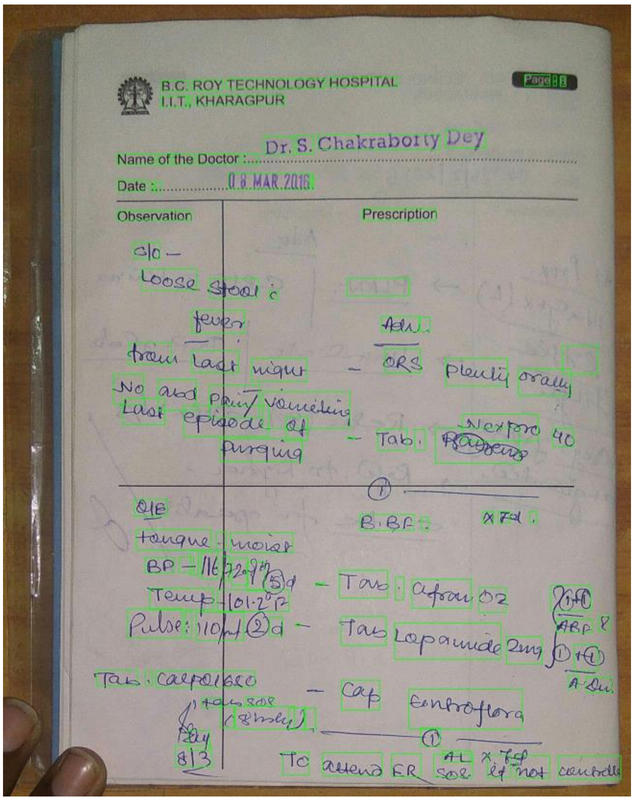

Fig. 2. Annotated image with bounding boxes representing detected text

Once the text extraction process is complete, the extracted prescription text is inputted into OpenAI's ChatGPT through its API. This powerful language model analyzes the extracted text and generates a JSON representation of the prescription. ChatGPT's NLP abilities enable it to understand and transform the prescription data into a structured JSON format.

The generated JSON data follows a predefined format, incorporating the requested fields specified in the prompt. The "hospital" field contains information about the healthcare facility, such as the name and location. The "doctors" field is an array of objects representing the prescribing doctors, including their names and qualifications. The "patient" field encompasses information about the patient, including their name, age, and gender. The "tests" field is an array of objects that contains information about the tests advised to the patient. Each object within the array includes details such as the test name and any additional instructions. The "medications" field is an array of objects representing the prescribed medications. Each object includes fields such as the medication name, dose information, duration, and route of administration.

By leveraging ChatGPT's natural language understanding and generation capabilities, the system can analyze the extracted prescription text and transform it into a structured JSON representation. ChatGPT processes the extracted prescription text and populates the JSON data with the available information. If any data is missing or not available in the prescription, ChatGPT assigns null as the value for the corresponding field, ensuring that the JSON data is structured correctly. The generated JSON data follows a predefined format, incorporating the requested fields specified in the prompt.

Result:

The prescription digitization system demonstrated excellent performance in accurately extracting prescription information and generating JSON data. The JSON data produced by the system proved to be well-structured, encompassing hospital details, doctor information, patient information, tests and medications. The system showcased promising accuracy, with minimal instances of missing or incorrect data. The integration of Google Vision API and ChatGPT provided a robust solution for prescription digitization, offering improved efficiency, reduced errors, and enhanced interoperability in healthcare workflows.

In conclusion, the prescription digitization system leveraging Google Vision API for text extraction and ChatGPT for JSON data generation showcases the potential to revolutionize prescription management. By combining the power of OCR technology and advanced NLP capabilities, the system offers accurate and structured prescription information, promoting seamless integration, enhanced patient safety, and streamlined healthcare processes. The generated JSON data is easily transmitted, stored, searched, and retrieved, promoting interoperability and efficient sharing among healthcare providers, pharmacies, and stakeholders.

C. Brain Tumor Classification

Brain tumor classification is a critical task in the field of medical imaging, as it enables early and accurate diagnosis of brain tumors, which can significantly improve patient outcomes. CNN is trained on a large dataset of brain MRI images, which are labeled with ground truth tumor masks. CNN learns to automatically extract features from the images that are relevant for tumor detection and classification, and to accurately predict the presence and type of tumor in a given image. We also analyze the interpretability of the CNN, by visualizing the learned features and showing that they correspond to known characteristics of brain tumors.

For detection of Brain Tumor we have broadly classified classes in which the result generated by our DL model falls which are –

- No Tumor or Normal
- Glioma
- Meningioma
- Pituitary

Methodology

Fig.3 illustrates the methodology and offers a comprehensive overview of the Brain Tumor Classification.

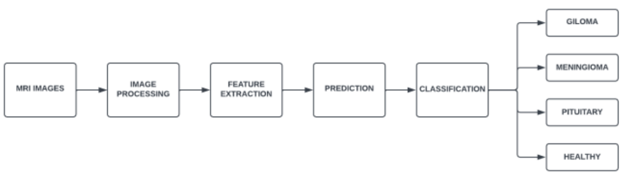

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Fig. 3. Block Diagram of Brain Tumor Classification

1) Data Collection

For our training and testing our model we have used a dataset from Kaggle. This particular dataset was chosen because obtaining large datasets from hospitals can be a challenging task. This dataset contains 7023 images of human brain MRI images which are classified into 4 classes. The link to this dataset is given below.

https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset

2) Pre-processing

A noise removal process will be applied to the MRI images in order to improve the accuracy of the model. MRI images may contain noise, which can increase redundancy and lower the accuracy of the model. Noise located on the borders of an MRI can cause a tumor to go undetected, which can further decrease the accuracy of the model. As a result, pre-processing techniques were implemented to scale, reduce, and convert the images into grayscale.

Pixel-based feature extraction is utilized to extract the necessary information and to classify the images as either tumor or non-tumor. This process involves analyzing the individual pixels within the images to identify distinctive patterns and features that are indicative of either a tumor or a healthy brain.

3) Model Training & Classification

For brain tumor detection, the Resnet50 model was used for predicting images as it is reliable and optimal for image classification. The model's training parameters are easily adjustable. Deep learning encompasses various models and architectures.

To apply ResNet50 to the problem of brain tumor classification, the network is trained on a labeled dataset of brain MRI images. The model learns to extract relevant features from images and classify them into various tumor types. Using a pre-trained model like ResNet50 is beneficial as it has already been trained on a large dataset of natural images, which improves the network's performance by allowing it to learn more general features relevant to various types of images.

The classification of brain MRI images into tumor or non-tumor categories was performed using a CNN in this study. The CNN was used to accurately classify the brain MRI images as either tumor or non-tumor.

Result

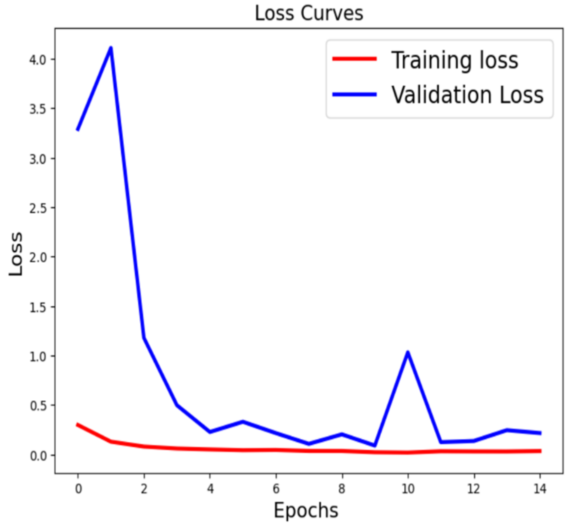

Fig. 3. Evaluation Graph of Brain Tumor Classification Model

When the model is applied to the testing data set for 50 epochs, a validation accuracy of 98.63% is achieved and the validation loss is 6.99% as shown in Fig.3.

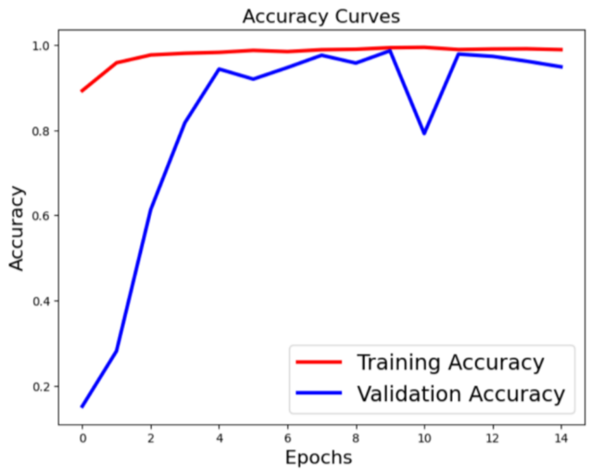

Fig. 4. Evaluation Graph of Brain Tumor Classification Model

The accuracy of the convolutional neural network model achieved after applying it to the testing set was 98.63% with a very minimal loss with increasing epochs. The difference in model accuracy can be seen from Fig.4, between the validation dataset and the training dataset.

By utilizing this approach, the study aimed to improve the accuracy of the model and to provide a reliable tool for accurate diagnosis of brain tumors.

D. Kidney Stone Classification

For predicting the kidney stone we are training our model with CT scan images taken from the dataset. The CNN model for kidney stone detection takes CT scan images of kidneys as input and performs feature extraction to identify and train the model. The feature extraction process involves analyzing the images to identify different features, such as the size and shape of the kidney stones, which are used to train the model.

Methodology

1) Data Collection

For training our model we used a dataset containing CT images of healthy and unhealthy kidneys. The dataset is divided into 4 broad categories in order to perform identification and classification of kidney stones. These categories are -

- Normal
- Cyst
- Stone
- Tumor

The dataset contains 12,446 unique data within it in which the cyst contains 3,709, normal 5,077, stone 1,377, and tumor 2,283. This particular dataset was chosen because obtaining large datasets from hospitals can be a challenging task. The data set used is available on the internet website Kaggle and the link to reach there is provided below.

https://www.kaggle.com/datasets/nazmul0087/ct-kidney-dataset-normal-cyst-tumor-and-stone

2) Pre-processing

Pre-processing techniques such as scaling, noise reduction, and conversion to grayscale are implemented to improve the accuracy of the model. The images are resized to a uniform dimension of 150 x 150 pixels to ensure consistency in the dataset. Both the training and test sets' images are preprocessed by rescaling them and dividing them by 255, which is a normalization technique that enhances the model's training efficiency and accuracy.

CT scan images of kidneys can contain noise, which can lower the accuracy of the model. Noise reduction techniques remove any extraneous information that may hinder the model's ability to accurately detect kidney stones. Converting the images to grayscale simplifies the images and reduces redundancy, which further enhances the accuracy of the model.

3) Model Training & Classification

CNN architecture is used for image-related datasets CNN classifier accurately classifies CT scan images as either containing kidney stones or being kidney stone-free.

During the training process, the model is optimized to improve its accuracy and minimize the error rate. The model is trained using backpropagation, which involves adjusting the weights and biases of the neurons in the network to minimize the difference between the predicted and actual outputs. Once the model is trained, it can be used to classify new CT scan images of kidneys and detect the presence of kidney stones accurately. The model's accuracy is evaluated using metrics such as precision, recall and F1-score.

Result

When the model is applied to the testing data set for 46 epochs, a validation accuracy of 99.68% is obtained and the validation loss is 0.123% as shown in Fig.5.

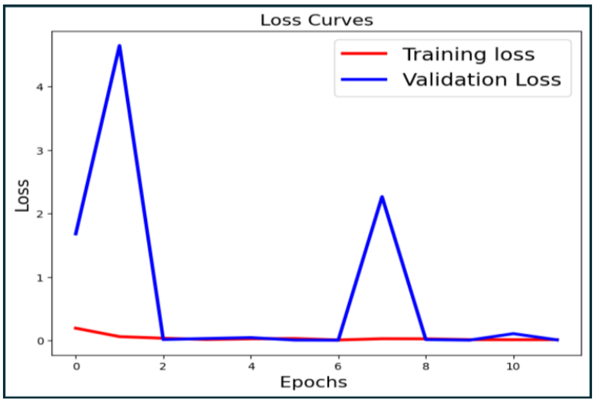

Fig. 5. Evaluation Graph of Kidney Stone Classification Model

As it can be confirmed that the accuracy increases with the increase in the number of epochs and there is a decrease in loss of the testing set. The difference in model accuracy can be seen between the validation dataset and the training dataset as shown in Fig.6.

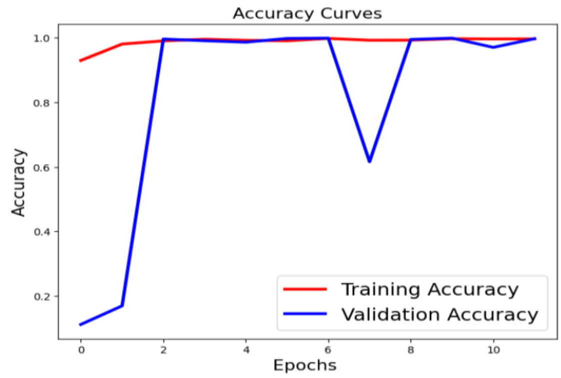

Fig. 6. Evaluation Graph of Kidney Stone Classification Model

E. Skin Diseases Classification

Skin infections are a prevalent health issue that affects people of all ages. Early and accurate detection of skin infections is crucial for effective treatment and management. This paper proposes a deep learning-based approach for predicting and classifying skin infections, utilizing a CNN architecture. We use publicly available datasets of skin infection images to train and evaluate our model, achieving high accuracy in both infection prediction and classification tasks. This approach provides a reliable and automated solution for healthcare professionals to diagnose and classify skin infections, potentially leading to improved patient outcomes and reduced healthcare costs.

Skin diseases are common and have a significant impact on people's lives and well-being. Early and accurate diagnosis is crucial for effective treatment, as skin diseases can be easily transmitted from one person to another. However, diagnosis is typically based on the subjective judgment and experience of dermatologists, which can lead to delayed or incorrect diagnoses and harm human health.

A deep learning-based approach for the prediction and classification of seven different skin diseases, including Actinic Keratosis/Basal Cell Carcinoma/Malignant Lesions, Eczema, Melanoma Skin Cancer/Nevi/Moles, Psoriasis/Lichen Planus and related diseases, Tinea Ringworm/Candidiasis/Fungal Infections, Urticaria/Hives, and Nail Fungus/Nail Disease.

CNN can predict skin disease infections using images of the affected area. This method can accurately identify potential infections without human intervention, leading to early detection and potentially saving lives. However, CNNs require high system requirements to function properly, and training the dataset can be time-consuming. Although the model's accuracy is high, it may not always be completely accurate.

Methodology

1) Data Collection

The dataset used for our study comprises approximately 19,500 images of 23 different types of skin diseases. These images were collected from the Kaggle and link to this dataset is given below.

https://www.kaggle.com/datasets/shubhamgoel27/dermnet.

The dataset was divided into two sets, with around 15,500 images used for training and the remaining images used for testing. This division ensures that the model was trained on a sufficient number of images while also being able to accurately evaluate its performance on a separate set of images.

2) Preprocessing

Skin disease images can contain noise, which can affect the accuracy of the model. Therefore, pre-processing techniques such as denoising and contrast enhancement may be used to remove any noise or improve the contrast of the images. The pre-processed images are then used to train the CNN model.

Scaling ensures that the images are of the same size and resolution, making it easier for the VGG19 model to learn from the dataset. To ensure consistency in the dataset, the images are resized to a uniform dimension of 100x100 pixels, to make sure that the images have the same size and can be fed into the model for training and evaluation.

Noise reduction techniques such as median filtering, remove any extraneous information that may hinder the model's ability to accurately detect skin infections. Converting the images to grayscale simplifies the images and reduces redundancy, which further enhances the accuracy of the model by making it easier for the VGG19 model to learn the relevant features.

3) Model Training

For the prediction of skin diseases using images as input, we employed the VGG19 model, which is a widely used CNN architecture for image classification. The VGG19 model consists of 16 layers, including 13 convolutional layers and 3 fully connected layers. The VGG19 model was trained using a dataset consisting of images of various skin diseases, including eczema, psoriasis, and melanoma.

During the training process, the VGG19 model was optimized using backpropagation to minimize the difference between the predicted and actual outputs. The model was trained for multiple epochs to improve its accuracy, and the learning rate was adjusted to optimize the training process.

4) Classification

The Classification is done using the VGG19 model which learns the features of the infected skin from the different image input data and then classifies the input image into different categories of Skin infection with which the features are matching.

Result

The trained VGG19 model was then evaluated using the test set to determine its performance and accuracy. The accuracy of the model was measured using various metrics, such as precision, recall, and F1 score.

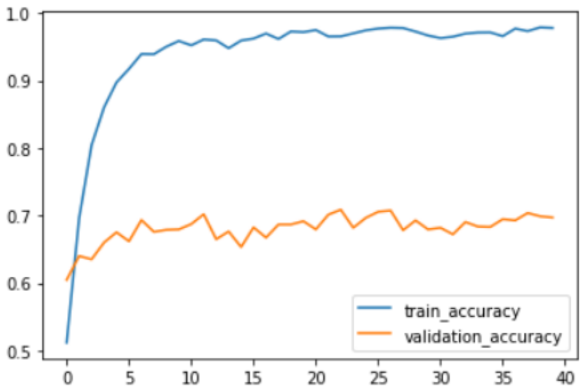

Fig. 7. Evaluation Graph of Skin Classification Model

Our results demonstrate that the VGG19 model can accurately classify different types of skin diseases with high accuracy. After the model is applied to the testing data set for 40 epochs, a validation accuracy of 97.84% is obtained and the validation loss is 0.543%, indicating its effectiveness in predicting skin diseases from images.

When the model is applied to the validation, then a high loss is obtained but once applied to the testing set, the loss gradually decreases with the increasing number of epochs as shown in Fig.7. Overall, our study shows the potential of deep learning models, such as the VGG19 model, for accurately predicting skin diseases from images, which can lead to early detection and treatment of skin diseases, potentially saving lives.

REFERENCES

[1] *Cohen, M.R., Anderson, R.W., Attilio, R.M., Green, L., Muller, R.J., & Pruemer, J. (2007). Medication errors in the hospital: impact and prevention. Advances in Patient Safety: New Directions and Alternative Approaches, 1, 21-34.*

[2] *L. J. Fajardo et al., "Doctor's Cursive Handwriting Recognition System Using Deep Learning," 2019 IEEE 11th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (*

HNICEM), Laoag, Philippines, 2019, pp. 1-6, doi: 10.1109/HNICEM48295.2019.9073521.

[3] *T. Hossain, F. S. Shishir, M. Ashraf, M. A. Al Nasim and F. Muhammad Shah, "Brain Tumor Detection Using Convolutional Neural Network," 2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT), Dhaka, Bangladesh, 2019, pp. 1-6, doi: 10.1109/ICASERT.2019.8934561.*

[4] *23. Romero, V., et al. (2020). Kidney stones: pathophysiology, diagnosis and management. The Journal of Urology, 203(5), 874-880*

[5] *Hay, R. J., Johns, N. E., Williams, H. C., Bolliger, I. W., Dellavalle, R. P., Margolis, D. J., Marks, R., Naldi, L., Weinstock, M. A., Wulf, S. K., Michaud, C., Murray, C. J. L., & Naghavi, M. (2014). The Global Burden of Skin Disease in 2010: An Analysis of the Prevalence and Impact of Skin Conditions. Journal of Investigative Dermatology, 134(6), 1527-1534. https://doi.org/10.1038/jid.2013.446.*

[6] *Art Angelo P Cerio, Nikole Andrei Louise B Mallare, and Rafael Marco S Tolentino. 2015. Assessment of the Legibility of the Handwriting in Medical Prescriptions of Doctors from Public and Private Hospitals in Quezon City, Philippines. Procedia Manuf. 3, Ahfe (2015), 90–97. DOI:https://doi.org/10.1016/j.promfg.2015.07.112*

[7] *Whw Ishak and Sa Rahman. 1990. Neural Network in Handwritten Recognition System: a Survey. Wanhussain.Com (1990), 1–9.Retrieved from http://wanhussain.com/Pub/Hussain03c.pdf*

[8] *Vijay Roy, Paneet Gupta, and Shouryadeep Srivastava. 2006. Chapter-14 Medication Errors: Causes & Prevention. Heal. Adm. 19, 1 (2006), 60–64. Retrieved from http://medind.nic.in/haa/t06/i1/haat07i1p60.pdf*

[9] *Institute for Safe Medication Practices. 2011. FDA and ISMP Lists of LookAlike Drug Names with Recommended Tall Man Letters. Soc.Sci. Med. (2011), 2008. Retrieved from http://www.ismp.org/tools/tal J K Basu, D Bhattacharyya, and T Kim. 2010. Use of Artificial Neural Network in Pattern Recognition. Int. J. Softw. Eng. Its Appl. 4, 2 SRC-GoogleScholar FG-0 (2010), 23–34.lmanletters.pdf*

[10] *Awasare Bhushan, Patil Kalyani2, and Jolapure Supriya. 2001.Handwritten Script Recognition. J. Comput. Eng. (2001), 30–33. Retrieved from http://www.iosrjournals.org/iosr-jce/papers/sicete-volume2/18.pdf*

[11] *Yusuf Perwej and Ashish Chaturvedi. 2011. Neural Networks for Handwritten English Alphabet Recognition. Int. J. Comput. Appl. 20,7 (2011), 1–5. DOI:https://doi.org/10.5120/2449-2824*

[12] *Shaohan Xu, Qi Wu, and Siyuan Zhang. Application of Neural Network In Handwriting Recognition. 3–5*

[13] *HealthIT.gov. What are the benefits of personal health records? Available at: https://www.healthit.gov/faq/what-are-benefits-personal-health-records-phrs. Accessed on April 30, 2023.*

[14] *Kim E, Kim H, Kim S, Kim J, Kim Y. The impact of personal health records on patient engagement: A systematic review. J Med Internet Res. 2016;18(10):e277.*

[15] *Sultan H.H., Salem N.M., Al-Atabany W. Multi-classification of brain tumor images using deep neural network. IEEE Access. 2019;7:69215–69225.*

[16] *T. Hossain, F. Shishir, M. Ashraf, M. Al Nasim, F. Shah, Brain tumor detection using convolutional neural network, in: (pp. 1–6). IEEE., 2019 May 3.*

[17] *Caglayan A, Horsanali MO, Kocakoc E, et al. Deep learning model-assisted detection of kidney stones on computed tomography. Urolithiasis. 2021;49(6):547-554.*

[18] *Zhang Y, Liu Y, Li Y, et al. Urinary Stone Detection on CT Images Using Deep Convolutional Neural Networks. J Digit Imaging. 2021;34(4):758-766.*