Early Eye Jaundice Diagnosis– Neural Network-Based Detection and Classification for Timely Medical Care

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Abstract

The skin and eyes turn yellow because of the excess of bilirubin and the diagnosis should be performed in time to avoid complications and save the life. These are classical procedures, whereby time consuming and intangible blood tests will be necessitated. It is a proposed method that entails Methods using Image Processing and Machine Learning to identify without invasive procedures. It saves images of faces and under controlled light as well as it preprocessed the images using methods such as color normalization and darkening contrasts; features such as skin tones and eye color are identified in transformation of color space (RGB). Machine learning Model to forecast the extent and existence of jaundice are educated on jaundiced and non-jaundiced clients. The ML algorithms assessing accuracy are the Convolution Neural Networks (CNNs). The technique is sensitive, specific and it is a good alternative to the outdated diagnostic procedures, particularly within the rural healthcare systems and telemedicine applications.

Keywords- yellowing of the skin and eyes, yellow pigment in the blood, data preparation, neural network for image analysis, medical care.

1. Introduction

Yellowing of the skin and eyes is a medical condition characterized by the yellowing of the skin and eyes, caused by an increased level of bilirubin in the body. Bilirubin is a yellow pigment produced during the natural breakdown of red blood cells. Early detection and proper treatment of jaundice are crucial, particularly for newborns and patients with liver-related disorders, as timely intervention can help prevent serious complications. The conventional ways of identifying jaundice include blood tests used to determine bilirubin levels. Although they are effective, the tests are invasive, time-consuming and uncomfortable to perform especially on infants. Over the past few years, technology has advanced and has provided a pathway of the non-invasive methods of medical condition detection. Image processing and machine learning are one of the promising ways of detecting jaundice. These approaches capitalize on the capabilities of digital pictures and smart algorithms to detect and scan the indicators of jaundice based on a photograph of the face of a person. Image processing refers to the act of manipulating and analyzing digital images in order to draw meaningful information. To detect jaundice, the face image is taken under controlled lighting conditions so that the image can be consistent and accurate. The collected images are first preprocessed to enhance features that indicate jaundice. This step includes techniques such as color normalization, contrast enhancement, and noise reduction, which improve image quality and highlight important details like skin tone and the color of the sclera. After preprocessing, the next step is feature extraction, where the images are transformed into a format that can be easily interpreted by machine learning algorithms. The yellowish discoloration associated with jaundice is highlighted and separated by adjusting the color space of the images. This involves converting images from RGB (Red, Green, Blue) to other color spaces such as HSV (Hue, Saturation, Value) and YCrCb (luminance and chrominance

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components). These transformations help in better identifying color variations related to jaundice. Additionally, statistical analysis is performed to measure and quantify these color features.

2. Related Work

The first few weeks of newborns experience jaundice or hyperbilirubinemia. Jaundice occurs due to an increased level of bilirubin in the blood. Elevated bilirubin levels can be toxic to brain cells, and in severe cases, it may lead to a condition known as acute bilirubin encephalopathy. The condition brings about brain trauma that results in kernicterus. Critical situations can be avoided by treating the diagnosis in time. Numerous studies have proposed jaundice diagnosis methods based on machine learning and image processing techniques. Image processing is an efficient, cost-effective, and user-friendly tool that is widely used in various medical applications, including MRI, X-ray, and CT scan analysis [1]. This paper presents recent non-invasive approaches for diagnosing jaundice, utilizing optical technologies to estimate bilirubin levels without the need for invasive procedures or blood tests. It uses harmless light that is not invasive on the skin. This study aims at coming up with a non-invasive procedure that will aid medical practitioners in timely diagnosis of jaundice. The AI methodologies assist in detecting with a lot of precision. The system is able to produce a continuous check at the level of the RGB of the skin and sclera in order to identify it early. In addition, our system is non-invasive and therefore reduces the suffering that is created by the conventional invasive procedures [2]. The system supports mobile healthcare applications by enabling non-invasive detection of neonatal jaundice using image processing techniques that analyze skin color changes, which typically appear within the first week after birth. The nervous system contains bilirubin which may cause brain damage. To overcome this issue, the most effective way of collecting blood tests is uncomfortable to babies to avoid the pain [3]. One of the most widely used methods for detecting jaundice is blood testing, which measures the concentration of bilirubin in the blood. Although this method is highly accurate, it is invasive, time-consuming, and often requires access to laboratory facilities that may not be readily available. To overcome these limitations, modern approaches increasingly rely on machine learning and image processing techniques. These methods can identify visible signs such as discoloration of the skin and eyes from digital images, enabling fast, automated, and non-invasive detection. This reduces dependence on laboratory tests and offers a cost-effective solution for large-scale screening, especially in remote and underserved areas [4]. Technology advancement has made jaundice a malfunctioned disorder that has many symptoms and thus has non-invasive system to help detect jaundice early and prescribe medication accordingly. The non-invasive procedures entail CNN algorithm of correct identification by Image processing techniques [5].

3. Materials and Methods

Neonatal jaundice is a common ailment that has been plaguing thousands of infants all over the world. In India 1 out of every six term and 1 out of every eight preterm babies acquire jaundice during the first week of birth. Otherwise, jaundice may be life threatening causing brain injury, deafness and death unless that can be detected and treated early. The world rates of severe cases of neonatal jaundice are estimated to be 481,000 of which more than 114,000 are fatalities. Moreover, most of the victims are permanently disabled, and this aspect is what makes the early identification and intervention urgent. Current diagnostic tools are based on clinical observations as in bilirubin level which might lack accuracy at such a young age. The project will mitigate them by offering a non-invasive, accurate, and scalable method of the early detection of jaundice and hence lowering the mortality rate among the affected newborns, as well as other long-term health complications. Multi-Model Eye Jaundice Classification Framework (MMEJCF) is a model, which combines deep learning frameworks (MobileNet, Xception and DenseNet) with modified layers to detect jaundice through the use of retinal images. It is an innovative method, which carries the learning to use the available trained models and adapts them to the particular jaundice prediction. MMEJCF is able to capture the retinal images at the initial stages, and thus the medical practitioner is able to make the required moves on good time before the jaundice reaches some critical stages. The system will be implemented as a web application on the internet that the users will be in a position to post retinal pictures and they will be automatically classified. This will create some level of interdependence in that there will be a feedback loop created through which the system will be more

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precise and reliable with time. The lack of connection between the non-invasive diagnostics and earlier intervention will become bridged in the proposed system so that the medical workers could treat the cases of jaundice effectively. The proposed jaundice detection system utilizes machine learning and image processing techniques, incorporating Convolutional Neural Networks (CNN) and the XGBoost algorithm to improve detection accuracy. The system stores the skin and eye images of a patient in order to determine the indicators of jaundice making blood tests unnecessary. The XG Boost reminds the prediction and makes corrections on it based on significant features in CNN model such as change of color and texture. The method is sure to offer rapid, non-invasive and precise jaundice diagnosis where diagnosis is required early, and screening is done on a large scale particularly in the poor health institutions.

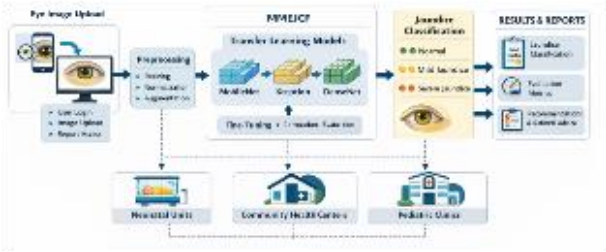

Fig. 1. System Architecture

Algorithm: Algorithm for Jaundice Detection

Input: Eye/retinal images

Output: Jaundice classification (Present / Absent / Severity)

Begin

- The eye image dataset is first loaded into the system for processing.
- The images are then preprocessed by resizing, normalizing pixel values, and applying data augmentation techniques to improve model performance.
- The dataset is divided into training, validation, and testing sets to ensure proper evaluation of the model.
- Pre-trained deep learning models such as MobileNet, Xception, and DenseNet are loaded to leverage transfer learning.
- The layers of these models are further optimized and fine tuned to enhance detection accuracy.
- The performance of the models is evaluated using metrics such as accuracy, precision, and recall.
- The best-performing model is selected based on these evaluation results.
- The selected model is then deployed in a web-based application for practical use.
- Users can upload an image, and the system processes it to predict the presence of jaundice.

End

Model building:

In this case a model should be developed and trained in a way to make predictions. Machine learning algorithm: The SVM, CNN and naive bayes algorithm shall be established and used in order to train the selected and cleaned features. To maximize performance, it is possible to optimize hyper parameters through such methods as cross validation. Model selection and training: In order to make the development process of the ML models simpler, the dataset is divided into two parts: training data and validation data. This way we can measure the generalizability of such a model by training it on a small set of data. (Training, feed the trained models on the test data to obtain the mean prediction to ascertain that we are obtaining the desired outcome). Model evaluation to assess the quality of the provided model carried out with the help of The using performance evaluation metrics such as accuracy, precision, recall, and F1-score. In order to test the effectiveness of a model with this item we could identify the true profile and fake profile and by performing continued monitoring We can discover the true profile and fake profile, by repeatedly executing the model until it could predict accurately.

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CNN Algorithm:

CNN is a classification model that does not use parameters and belongs to the supervised machine learning techniques. Consequently, there is a need to have predefined label or group of labels in the data. It is a form of instance-based learning method, since it does not generate a model as compared to most other classification schemes. Rather, it is an example based predictor. New training set can be constantly added to the algorithm. The figure2 explains the working principle of CNN.

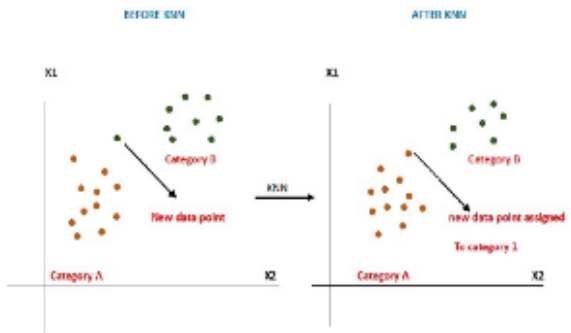

Fig. 2. Classification of new user profile using CNN

The algorithm provided below can be called the one that helps realize the way CNN operates.

i. Choose fixed number of neighbors also known as k.

ii. Find the Euclidean difference of them.

iii. **Euclidean Distance:**

$$d = \sqrt{(x2 - x1)2 + (y2 - y1)}$$

iv. choose the Neighbors with calculated Euclidean distance minimum.

v. The number of data points in each segment must be included in this group of K neighbors.

vi. Label the data points with the category that has the most neighbors.

suppose that in the above figure there exist two segments viz A and B, and that we now have a new data point X1, we must determine, in which of the two segments X1 will be found. To solve such a problem we require a CNN techniques. With the CNN algorithm we can easily label a group of people with their classes.

A. Modules Description

• **Retinal Image Acquisition:** Collects retinal images from the user, serving as the primary input for jaundice detection. Images can be captured using low-cost, portable devices suitable for various healthcare environments.

•**Preprocessing:** Prepares retinal images by resizing, normalizing, and enhancing them to highlight relevant features, ensuring consistency and noise reduction.

•**Feature Extraction:** Utilizes deep learning techniques to ex tract important features from retinal images using transfer learning models such as MobileNet, Xception, and DenseNet.

• **Classification:** Classifies extracted features into different stages of jaundice severity using a trained neural network model, providing immediate insights.

• **Web Application Interface:** The system enables users to upload images and obtain real-time classification results, while also allowing the collection of user feedback.

• **Model Feedback Loop:** Incorporates user feedback to continuously improve model accuracy and detection performance.

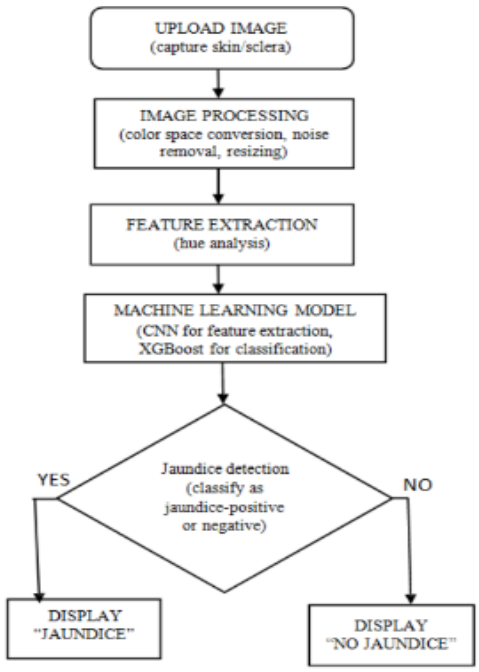

Fig. 3. Flow of Project

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4. Results and Discussion

The jaundice detection system involves several stages, including dataset preparation, image preprocessing, feature extraction, the application of a Convolutional Neural Network (CNN) model, jaundice detection, and result validation.

A. Jaundice Detection System Process

The jaundice detection system consists of multiple stages, including dataset preparation, preprocessing, feature extraction, CNN-based classification, and result validation.

1) Image Upload

• The raw image is first uploaded and then undergoes preprocessing, which includes resizing and normalization to enhance its features for accurate analysis.

• Record the skin and sclera of the patient at various lighting conditions. The dataset that is processed is of varying skin tones, ages as well as lighting.

2) Data Preparation

• The images are adjusted by modifying contrast, bright ness, and white balance to ensure consistent lighting conditions.

• The region of interest (ROI) is identified and segmented using techniques such as edge detection. Use filtering on the unwanted artifacts.

3) RGB Color Analysis (Skin/Eye Detection)

• The color variations associated with jaundice are then analyzed, where higher red (R) and green (G) values and lower blue (B) values indicate a yellowish appearance.

• The system computes color ratios, such as the R/G ratio (which is higher in jaundiced skin) and the B/Y ratio (which is lower in yellowish skin), to assist in detection. • The image can be converted into alternative color spaces, such as HSV, to improve detection accuracy. The extracted features are then fed into a machine learning model to determine the presence of jaundice and assess its severity, if present.

4) CNN-Based Processing

• The CNN automatically extracts deep features from images to detect jaundice.

• It is highly effective in image analysis, as it automatically captures spatial variations in features such as color differences, texture patterns, and the intensity of yellow discoloration.

• The model extracts features using convolutional layers, reduces dimensionality through pooling layers, and learns classification patterns using fully connected layers

. • The CNN ensures that important image-based features are effectively captured to enable accurate detection of jaundice.

5) Result Validation

• If the uploaded image indicates the presence of jaundice, the system displays “Jaundice” along with the corresponding confidence level.

• If jaundice is not detected in the uploaded image, the system outputs “No Jaundice” along with the corresponding confidence level.

The proposed jaundice detection system demonstrated strong performance, highlighting the effectiveness of image processing techniques in achieving accurate and reliable diagnosis. The model, trained on a diverse set of skin images, achieved an overall accuracy of 93.

Preprocessing steps such as image resizing, normalization, and data augmentation played a crucial role in improving model performance by reducing overfitting and enabling the system to handle variations in image conditions. The developed web application featured a user-friendly interface, providing fast and accurate predictions with an average response time of 3–5 seconds.

The system was evaluated using images with varying lighting conditions, skin tones, and quality levels. While it performed well overall, slightly better results were observed for lighter skin tones. The cloud-based deployment ensured scalability, allowing multiple users to access the system simultaneously without performance degradation.

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Despite its effectiveness, the system has certain limitations, including potential bias toward lighter skin tones and limited interpretability of the model's decision-making process. Future work will focus on improving dataset diversity and incorporating explainable AI techniques to enhance both accuracy and user trust.

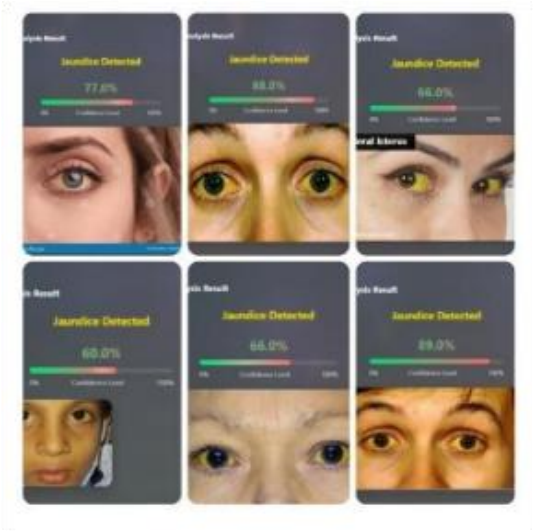

Fig. 4. a jaundice affected images

Fig. 5. Jaundice not affected

Out of the above dataset of Jaundice Detection, we have sampled 900 images. Out of that, we obtain the above image tests as jaundice prediction and normal (no jaundice).

5. Conclusion

The jaundice detection system shows that machine learning and image processing can be efficiently applied to come up with a user-friendly, fast, and non-invasive diagnostic solution. With the help of a Convolutional Neural Network (CNN), the system was able to classify images into two categories normal and jaundiced with a 93% accuracy. Furthermore, pre-processing like resizing, normalization, and data augmentation are also important factors that helped the model to be more stable and consistent with different image conditions. Flask Web Deployment also makes the system available and scalable to allow the practitioners and people utilizing the tool to pick up the earlier detection of resource- poor environments. Despite the conclusion made that the system was functioning reasonably well, some of the issues it was facing such as a biasness in the outcomes of the prediction of a darker skin color, as well as the inability to interpret model predictions on outputs is a pointer to the improvement that will occur in the future. The next-generation research involves the enhancement of diversity of datasets, including explainable AI methods, and the utilization of potential of systems by using multimodal data.

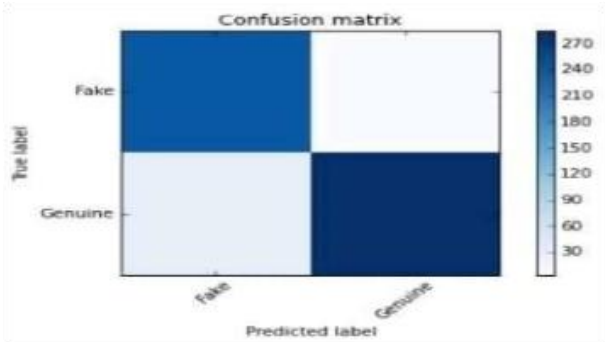

Fig. 6. After doing the normalization of the confusion matrix.

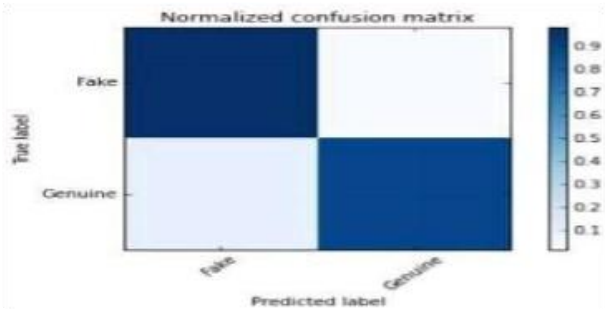

Fig. 7. Normalized Confusion Matrix

The category of reports has been introduced to establish the fake and genuine profile precision index, recall, f1-score and support vector. The ultimate experiment results are as follows that explain the values of false positive and true positive.

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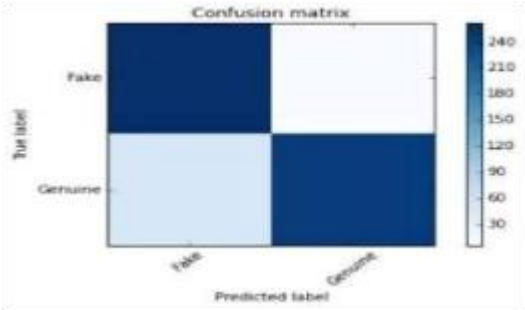

Fig. 8. Confusion Matrix

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