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Performance of Fast Learning Approach to Predicting Black Fungus Diseases

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Abstract: Microscopic examination can be used to make a preliminary diagnosis of fungal infections. Due to their apparent similarities, it frequently does not allow for the species to be identified clearly. Therefore, additional biochemical tests are typically required. This adds extra expenses and can make the identification process last up to ten days. Given the high death rate for immunosuppressed patients, such a delay in the adoption of targeted therapy could have serious consequences. The fast learning network method is an alternative that provides information with a unique approach to predicting black fungus. The experimental results of prediction showed that the performance of the fast learning method is superior as compared with the five algorithms used in this paper.

Keywords: black fungus, COVID-19, fast learning machine, machine learning, Microscopic

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1. Introduction

Fear related to black fungus may end up being a terrible public health issue as incidences of the disease have increased in the middle of the COVID-19 pandemic. A dangerous fungus infection that has lately emerged as a hazard to COVID-19 survivors is known as a black fungus. In India during the COVID-19 pandemic, the frequency of black fungus is eighty times higher [1, 2]. Numerous nations, including Bangladesh, Pakistan, Russia, Iran, and Brazil, have been impacted by the black fungus linked to COVID-19.[3–7].

As inhaling fungal spores from the environment can result in illness in the lung and sinuses, black fungus affects people through contact with the fungal spores [8]. Immunosuppression-related factors, such as hematologic malignancy, hematopoietic stem cell transplantation (HSCT), solid organ transplantation (SOT), and diabetes mellitus, are associated with high-risk black fungus infections [9, 10]. The patient's underlying medical issues are thought to be a significant risk factor for developing a primary black fungus infection [11, 12].

The rhino orbital cerebral type infection, which is now commonly associated with COVID-19 and manifests clinically around the nose, eye, and brain [13], is the most common form of black fungus infection nowadays.

Currently, it is acknowledged as a risk factor for black fungus infection when corticosteroid medication is used to treat COVID-19 patients with diabetes mellitus [14, 15]. According to a study, COVID-19 patients who had pulmonary mucormycosis The rhino orbital cerebral type infection, which is now commonly associated with COVID-19 and manifests clinically around the nose, eye, and brain [13], is the most common form of black fungus infection nowadays. Currently, it is acknowledged as a risk factor for black fungus infection when corticosteroid medication is used to treat COVID-19 patients with diabetes mellitus [14, 15]. According to a study, COVID-19 patients who had pulmonary mucormycosis were primarily affected by this condition because of their weakened immune systems [16, 17]. Vessel thrombosis, followed by tissue necrosis, is a pathogenic feature of the black fungus that accounts for about 54% of mortality [18, 19]. Avoiding the risk factors is the only way to avoid contracting black fungus during COVID-19. Black fungus is currently unavoidable although the COVI ID-19 immunization campaign has begun. As a result, it's crucial to start treatment and diagnosies quickly.

Machine learning techniques have attracted a lot of attention from the research community [20]. As compared to previous processes for data categorization, machine learning techniques have the potential to provide high classification accuracy, as described in multiple recent research[21]. It is crucial to achievinge discernible accuracy in prediction because doing so can result in suitable protection. Depending on the learning techniques used, the accuracy of the predictions may change. It is crucial to identify devices capable of delivering high- accuracy of prediction in black fungus illnesses. The degree of prediction accuracy attained in the initial effort is compared to that of the earlier studies. Creating a pipeline of classification algorithms based on machine learning techniques for the operational diagnosis of black fungus illness is the goal of this endeavor.

The objective of this study is to develop a quick learning network model that can forecast infections caused by a black fungus (FLN). The features of this cutting-edge machine learning algorithm are simplicity, computational efficiency, and good learning performance [22]. Fast Learning Network performance was evaluated in comparison to Support Vector Machine (SVM) [23], Decision Tree (DT) [24], Extreme Learning Machine (ELM) [25], Random Forest regressor (RFR) [26], as well as K Nearest Neighbor (KNN) [27]. Following is the organization of the remaining text. In part 2, we talk about the strategy. The experimental findings are discussed in Section 3. In Section 4, a summary and suggestions are given.

2. Methodology

This section introduces the methods for constructing classifications of obesity disease using FLN approach. In subsection 3.1, we present the procedure of FLN based on obesity data. In subsection 3.2, we present the dataset. Assessment measures employed in the evaluation of our method are mentioned in subsection 3.3.

A. Fast Learning Networks

For prediction, we'll employ a particular kind of neural network, one with a single hidden layer and parallel connections between the input and output layers on one side and the hidden and output layers on the other. FLN is a cutting-edge variation of an extreme learning machine [28]. The hidden layer biases and input weights are generated at random in FLN, and the analytical weight values for the links between the output layer and the input layer as well as the weight values between the output node and the input nodes are computed using the least square method.

B.Dataset

The Digital Image of Fungus Species (DIFS) database provides 180 images (9 strains x 2 preparations x 10 photographs), each with a high resolution and a 16-bit intensity range [29].

C. Evaluation

The performance of our technique will be evaluated using the assessment metrics expressed in equations (1, 2, 3, and 4).

$$Accuracy = \left(\frac{TP+TN}{TP+TN+FP+FN}\right) * 100\% \quad (1)$$

$$Precision = \left(\frac{TP}{TP+FP}\right) * 100\% \quad (2)$$

$$Recall\ or\ sensitivity = \left(\frac{TP}{TP+FN}\right) * 100\% \quad (3)$$

$$F\text{-}measure = 2\left(\frac{Recall * Precision}{Precision+Recall}\right) * 100\% \quad (4)$$

A sample count known as a True Positive (T P) indicates that there is no black fungus illness present.

The number of samples in which it is anticipated that black fungal disease would not be present is known as True Negative (T N).

False negatives (F N) are samples that were taken but were reported as having been taken in the absence of a black fungus illness.

False Positive (F P) samples are those where black fungus illness is found but it wasn't expected to be there.

3. Experimental results

An empirical assessment of the FLN's propensity to forecast black fungus illness is provided in this section. For the classification of the black fungus illness dataset, we considered six machine learning algorithms: FLN, ELM, SVM, DecisionTree, RandomForestRegressor, and KNN. All the techniques were trained in and evaluated using MATLAB version 2019. Training (60%), testing (20%), and validation (20%) were the three categories for the experimental data. The sigmoid function was selected to deal with the nonlinear issue. This function is widely used in a hidden class due to the simple relationship between the function and its derivatives.

The accuracy of the six algorithms is shown in Figure 1. In terms of accuracy, FLN surpasses SVM, DT, ELM, RFR, and KNN. Additionally, the highest accuracy was acquired for all features, and in that case, FLN's accuracy was shown to be higher than 87%. With a performance of 80.77%, the RFR algorithm has the lowest efficiency.

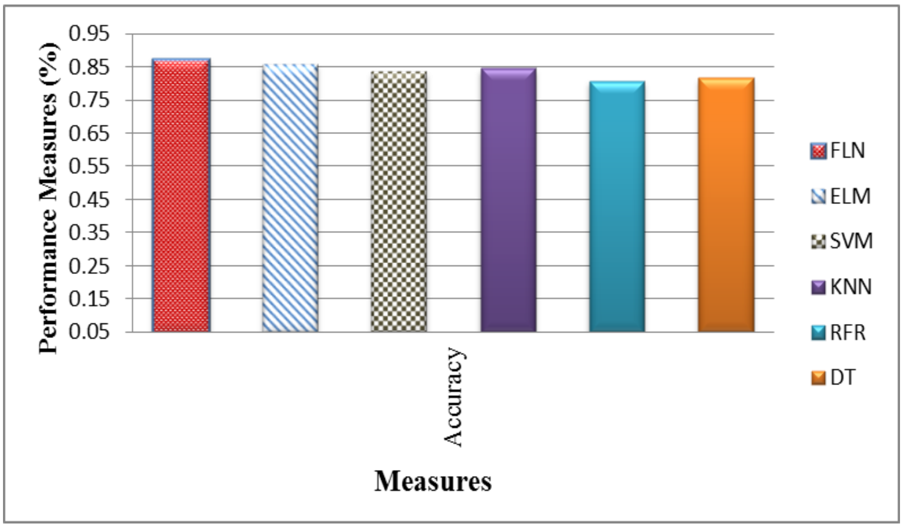

Figure 1.Accuracy measure of the machine learning approaches

In Figure 2, we demonstrate that the recall measure of the SVM outperforms that of the other machine learning models. ELM had a lower recall than KNN, FLN, DT, and RFR, which was evaluated at 76.90%.

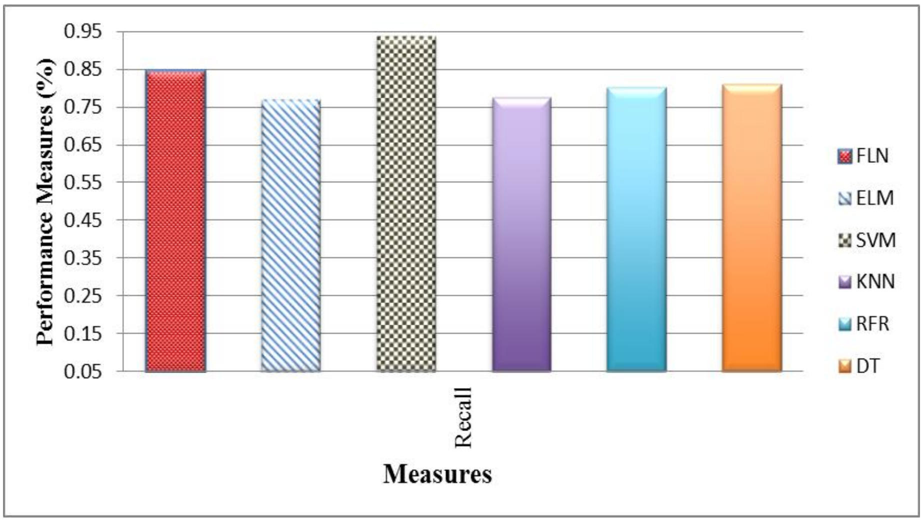

Figure 2. Recall measure of the machine learning approaches

The six models' precisions were computed. Figure.3 shows that compared to RFR, DT, KNN, SVM, and FLN, ELM is superior. Additionally, SVM precision is inferior to other methods, only achieving 72.67%

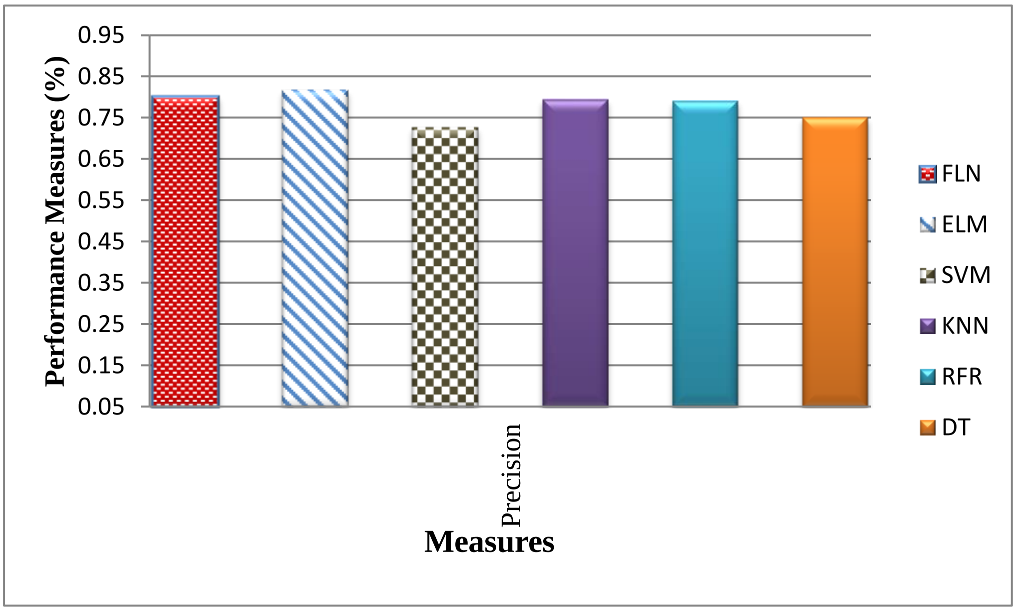

Figure 3. A precision measurement of the machine learning approaches

Figure 4 shows the results of the F-measure calculations for each of the six models. FLN outperformed other methods, achieving an F-measure of 83%. RFR performs better than ELM, SVM, KNN, and DT. ELM is also inferior to all algorithms in terms of F-measure.

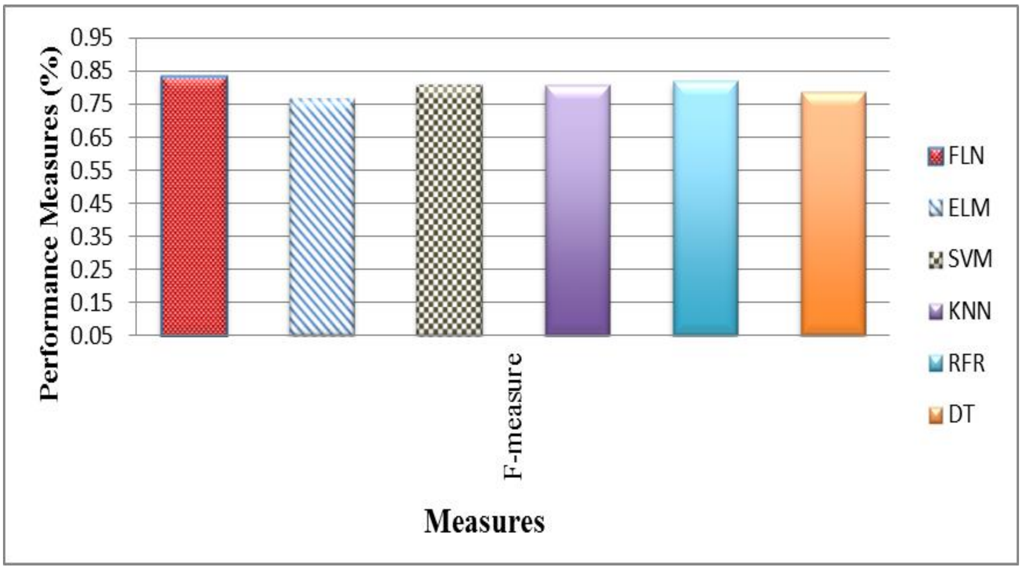

Figure 4. F-measure values of the machine learning approaches

4. Conclusion

This study describes a method for determining whether a black fungus is present or not using machine learning techniques. Predicting obesity disease may help patients receive better care and save lives. The FLN was compared with six machine learning approaches to predicting black fungus based on a variety of variables. Several metrics were used to evaluate and validate the strategies. The results showed that the FLN classifier produced the most accurate outcomes. In the future, feature selection will be used to enhance the algorithm's performance. Also, will be constructing a big dataset with many features to strengthen the prediction of black fungal diseases.

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