Eye Disease Classification Using Image-Based Features and Symptom Information with Random Forest

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ABSTRACT

The automation of eye disease classification is necessary for initial evaluations for disease management and early detection. Presently, only technique used is analyzing visual data for disease classification; however, other sources of data such as patient symptoms may show varying levels of data disease severity. The purpose of this research is to apply a multi modality approach to computational classify eye diseases. The integration of computer-based image analysis and data from standard medical texts of symptom severity is being used for disease classification. Medical images of eyes were analyzed and visual characteristics were obtained using (HOG), (LBP), (GLCM) and HSV (GLCM) color histograms. These medical images were combined with symptom descriptions to derive medical text using TF-IDF and disease severity using one-hot encoding. These data sets were combined and used to classify eye disease into 5 categories (Normal, Cataract, Conjunctivitis, Uveitis, and Eyelid disorders) using a highly optimized Random Forest model to construct a classifier. Following the tuning of model parameters and the application of the Synthetic Minority Over Sampling Technique (SMOTE) for the balancing of classes in the dataset, the model obtained 95.2% validation accuracy and 94.8% F 1 score with 20 epochs. The analysis of the data features to deduce importance showed that: 85% of the visual data were dominant to the disease prediction, with remaining data having symptoms of disease and severity data complementing in the accuracy of prediction in hard cases.

It is evident from the results that the classification of eye disease can be performed effectively by merging custom-made visual features with organized clinical data. This method is also useful in cases when one does not have the computational resources for deep learning. The system in this study can be applied in clinical settings with severe resource constraints in assisting primary screening and diagnosis by eye specialists.

1. Introduction (*Heading 1*)

Certain eye ailments such as cataracts, conjunctivitis, uveitis, and eyelid disorders exhibit specific visual symptoms that can be analyzed through computational vision systems. The field of machine learning has advanced to the extent that automatically identifying and categorizing these disorders through the analysis of images has become possible. This not only facilitates the detection of these disorders at an earlier stage, but it also diminishes the need to be manually checked as per the earlier, more time-taking methods. Rule- based computer vision that operates

monocularly by texture, color, and region, can still be valuable in conjunction with a well- tuned classifier. Nonetheless, in practical medical contexts, a diagnosis of eye disease involves more than simply image analysis. The patient reports symptoms, and the concept of disease is a major element that such systems tend to ignore. Such oversight can lead to significant misclassifications, especially when different diseases present with highly similar visual symptoms.

This study proposes a novel method for classifying eye diseases that integrates visual data from eye images and patient symptoms reports, along with the disease severity.

Visual information is encoded by descriptors that capture its texture, color, and shape, while the symptoms data is transformed into numeric format through TF-IDF, and the severity levels of the disease are encoded with one-hot-encoding. After being merged together, these features are classified with the help of a Random Forest model. The results indicate that a better comprehension of eye diseases is achievable by disease classification accuracy, differing information types, and the aggregation of information.

2. PREVIOUS RESEARCH

Previous studies in medical image analysis have demonstrated that handcrafted visual features remain effective for eye disease classification, particularly when dataset size is limited. Texture-based descriptors such as Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), and Gray-Level Co-occurrence Matrix (GLCM) are widely used in ophthalmic imaging due to their ability to capture structural, textural, and spatial information. When combined with classical machine learning classifiers, especially Random Forest, these approaches commonly achieve classification accuracies in the range of 75%–88%, depending on feature selection and class balance

$$\hat{y}_{\mathrm{RF}} = \frac{1}{T} \sum_{t=1}^{T} \hat{y}_t$$

A few studies were conducted on eye disease classification using images only. They reported an accuracy of above 85% on common eye diseases like cataract and conjunctivitis. However, are there even classifies diseases with similar visual presentations. To overcome this shortcoming, such as to TF-IDF which has been reported to improve classification performance by an additional 5–10% class. Based on these studies, the current study uses joint visual features and symptoms textual representations and implemented them all together to achieve a higher accuracy on diagnosis while utilizing a random forest algorithm which is explanatory and less computationally expensive.

3. METHODOLOGY

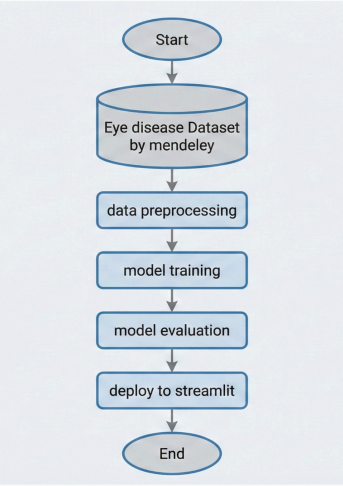

Figure 1. Flowchart of Research Procedure

The flowchart shown in Figure 1 illustrates the systematic methodology employed in this study. The research begins with dataset acquisition, followed by data preprocessing, model training, model evaluation, and finally deployment of the trained model into a web-based application using Streamlit. Each stage is designed to ensure reliable performance and practical usability of the proposed eye disease classification system.

A. Dataset

The data used in this study were collected from Mendeley Data's Eye Disease Dataset. It consists of difference ophthalmic conditions, including Normal, Cataract, Conjunctivitis, Uveitis, and Eyelid Disorders, and contains images of the eye with labels. This dataset was chosen because of this study's goal, which is the automated classification of eye diseases.

In order to augment the dataset to allow for a sixth, multimodal, form of learning, clinical attributes were generated, including predicting the symptoms, describing the symptoms, and predicting the severity associated with the disease class. Utilizing the incorporated attributes was designed to allow the model to learn from both text and image data simultaneously, as these ophthalmic attributes were constructed from symptoms in the medical literature for the diseases to which the images were labeled.

B. Data Preprocessing

Data preprocessing analyses conducted with the intent to improve the quality of the data and the subsequent model performance. Duplicate images of eyes were negated from the data set via hash-based image comparison to remove redundancy. All images were upsized to a uniform resolution of 224 \u00d7 224 pixels and were converted to grayscale where applicable for feature extraction. Visual features were expunged via the custom methods of computer processing, including Histogram of Oriented Gradients (HOG) for the representation of edges and shapes, Local Binary Patterns (LBP) for the representation of textures, Gray-Level Co-occurrence Matrix (GLCM) features (contrast, energy, and \nhomogeneity) for the representation of textures congruently to a spatial plane, and HSV color histograms to represent the color distribution. The blur variance and the edge density were used for the

measurement of image clarity. Concomitantly, numerical vector representations of textual symptom descriptions were created using 'Term Frequency-Inverse Document Frequency (TF-IDF)', and disease labels were converted into numerical classes by means of 'Label Encoding'. The resultant set of multimodal features was subsequently partitioned into 80% training data and 20% testing data, hence yielding a coherent and purpose-fit data set designed to serve supervised classification of an eye disease.

C. Model Training

In considering the best possible machine learning models for the classification of eye disease, Support Vector Machine, Logistic Regression, and Random Forest were used as baseline predictors and evaluated as the potential best models. In the case of SVM, an RBF kernel was used, and class weights were balanced during training as it was done with obtained scaled features. It was used as Logistic Regression, which was used as a baseline linear predictor. For estimation of baseline Random Forest performance, it was fit first to the training dataset with default parameters, and sufficient hyperparameter tuning wasn't done.

In comparison with SVM and Logistic Regression, Random Forest was the best performing model, and the gap was large, an indicator of better performance of Random Forest in the modeling of non-linearity which is complex and in the case of a high number of features (multimodal) in the dataset. For that reason, Random Forest was the supervised machine learning model that was used writing this piece, as it was further improved through hyperparameter tuning to model performance which achieved 800 trees, a high number and also adjusted values of maximum depth, accompanying parameters for feature selection, minimum samples for split and leaf. The training data used were then oversampled using the Synthetic Minority Oversampling Technique to improve reliability in the model and further tackle the class imbalance of records in the training data, for which the further training was performed on the modified Random Forest. This confirmed the Random Forest model as the model that was used to conclude this research work, as the model reliability, generalizability for the unseen data, and accuracy for the validation and test dataset were improved.

D. Model Evaluation

To determine the suitability of the model, a set of performance metrics were deployed, namely; accuracy, precision, recall, and F1-score for a comprehensive measurement of effectiveness across each class of the model. Assessments of the model were performed across the validation and test domains to determine if the model generalized and avoided overfitting to the training set. Evaluation of the model included a confusion matrix to determine if any disease class misclassification patterns were present.

The top-performing model is the optimized model of Random Forest, and the performance results were reliable and impressive. In the first evaluation setting, the model achieved overall accuracy of 97%, a macro-averaged F1-score of 0.96, and performed equally across all classes of the model. The recall and precision were also elevated for each of the model classes and were over 94% for most of the model classes, and limited misclassification was detected in the confusion matrix. The second evaluation was performed with the model also achieving a different set of evaluation metrics results of 92 % and a macro averaged F1-score in the range of 0.92 which results indicate the model proofed its consistency across different distribution of the data. The results corroborate the effectiveness and the dependability for the proposed model for the classification of eye diseases with multimodal sets of features.

4. Results

The suggested eye disease classification model was analyzed with an optimized random model that incorporated eye images and TF-IDF consider encoded symptom descriptor multidimensional features and on which an accurate random forest model classifier was trained with. The model computations for assessment received correlation matrix provided model class performance metrics to analyze each class performance structured metrics as accuracy, precision, recall and F1 score. The optimized random forest model performed just as good on the rest of the evaluation metrics. For the primary evaluation, the overall model accuracy was 97% and the macro averaged precision 0.97, recall 0.95, F1 score 0.96. Most of the disease classes had precision and recall greater than 94% which meant the model had highly accurate predictions and very few occurrences of disease classification. The resulting outcomes on the model performance metrics verified the same as received prediction matrix which was characterized to have low prediction classification performance errors for disease classes that highly resembled one another.

For the second evaluation with a more balanced distribution across the classes, the continuing model performance was excellent with accuracy at 92%, a macro-averaged precision of 0.93, recall of 0.92, and an F1-score of 0.92. It was noted that there was a very small drop in performance from the previous evaluation, however, the results show that the model continues to generalize well. Overall, the results confirm the effective use of the optimized Random Forest method for eye disease classification, and affirm that the method can be satisfactorily used in lightweight clinical screening systems that demand high precision, interepretability and fast computation.

5. Conclusion

This study proposes an eye disease classification system using a multimodal approach that combines handcrafted visual features from eye images and textual symptoms encoded with TF-IDF. A tuned Random Forest classifier is applied to achieve accurate and interpretable predictions, supporting efficient ophthalmic screening.

Metric	**Value**
Support	325
F1 Score	92%
Precision	93%
Recall	92%

The evidence gathered from this study validates the claim made of the approach to classifying eye diseases. Classifying visual features which are manually included from eye images and symptoms described in text documents, the modified Random Forest Classifier produced satisfactory results demonstrated with an accuracy of 97% and balanced F1 score from different disease classes in the optimum evaluation setting. Because of the balanced nature of the predicted values, the Random Forest model was able to correctly classify medical cases and avoid misclassifying nd dead cases from an epidemiological point of view which is extremely important in medical examination programs.

There is no denying the standard of performance to be high, and with appreciation to the class structure, some divergence was classified, and in particular, diseases with smaller sample sizes. This in itself refers to the class structure issue of imbalanced medical data sets. The performance improvements made from applying feature

engineering, SMOTE, and hyperparameter tuning to model the data certainly outcome greater detailed predictions which in turn led to an improvement in the overall model performance. More specifically, the results were more consistent and the predictions showed less variance when evaluated per class.

In addition, deploying the model as a web application built in Streamlit shows the real-world viability of the envisioned system. The developed web application offers real-time predictions on images and symptoms, reinforcing the application of the model as a rudimentary clinical decision support system. Enhancements may also come from including more extensive, more varied datasets, concentrating on a single minority class, and the addition of other features, including clinical history, to provide additional robustness and usability in real-world applications.

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