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ORIGINAL

Hybrid Machine Learning Approaches for Classification of Retinal Vascular Occlusions Using Multisource Clinical Text Data

Enfoques híbridos de aprendizaje automático para la clasificación de oclusiones vasculares retinianas mediante datos de texto clínico de múltiples fuentes.

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ABSTRACT

Predictive models that incorporate a variety of clinical data have grown in significance as a means of improving healthcare decision-making. There is still a sizable amount of unstructured patient data that is either in the form of handwritten records that have been digitized or free-text doctor notes. This research builds a framework for the two data sources, digital clinical notes and scanned handwritten notes to perform predictive analysis. The data chosen for the research is related to Painless sudden loss of vision which is considered to be a serious ophthalmic emergency and is frequently associated with retinal vascular occlusions. Improving patient outcomes and facilitating prompt intervention need early distinction between its primary causes, which are Central Retinal Artery Occlusion (CRAO), Central Retinal Vein Occlusion (CRVO), Branch Retinal Artery Occlusion (BRAO), and Branch Retinal Vein Occlusion (BRVO). In the first stage, the unstructured clinical data from the textual/scanned format are converted into one single structured data frame using natural language processing (NLP). Structured data is then evaluated with machine learning algorithms and tested with different variations in order to identify the model that delivers the highest predictive accuracy, guided by the characteristics of the clinical data itself.

Keywords: Predictive Models; Unstructured Clinical Data; Natural Language Processing (NLP); Retinal Vascular Occlusions; Predictive Accuracy.

RESUMEN

Los modelos predictivos que incorporan diversos datos clínicos han cobrado importancia para mejorar la toma de decisiones en el ámbito sanitario. Aún existe una cantidad considerable de datos no estructurados de pacientes, ya sea en forma de registros manuscritos digitalizados o de notas médicas en texto libre. Esta investigación establece un marco para ambas fuentes de datos (notas clínicas digitales y notas manuscritas escaneadas) para realizar análisis predictivos. Los datos seleccionados para la investigación se relacionan con la pérdida súbita de la visión indolora, considerada una urgencia oftalmológica grave y frecuentemente asociada a oclusiones vasculares retinianas. Para mejorar los resultados del paciente y facilitar una intervención rápida, es necesario distinguir tempranamente sus causas principales, que son la oclusión de la arteria central de la retina (OACR), la oclusión de la vena central de la retina (OVCR), la oclusión de una rama de la arteria retiniana (OABR) y la oclusión de una rama de la vena retiniana (OVBR). En la primera etapa, los datos clínicos no estructurados del formato textual/escaneado se convierten en un único marco de datos estructurado mediante procesamiento del lenguaje natural (PLN). Luego, los datos estructurados se evalúan con algoritmos de aprendizaje automático y se prueban con diferentes variaciones para identificar el modelo que ofrece la mayor precisión predictiva, guiado por las características de los propios datos clínicos.

Palabras clave: Modelos Predictivos; Datos Clínicos no Estructurados; Procesamiento del Lenguaje Natural (PLN), Oclusiones Vasculares Retinianas; Precisión Predictiva.

INTRODUCTION

The integration of machine learning into healthcare has shown remarkable potential to improve diagnostic accuracy, decision support, and patient outcomes. However, a major challenge in obtaining this potential lies in the nature of clinical data which exists in unstructured formats in most cases such as free text physician notes or scanned paper records. Such data are densely populated with clinical notes yet challenging for manipulation and analysis with traditional computational approaches.[1,2] To narrow this difference between unstructured clinical narratives and organized, machine-readable data artificial intelligence solutions have arisen, particularly in the field of clinical Natural Language Processing (NLP). Even handwritten or scanned PSLOV papers can be processed and rendered viable for computational analysis when paired with a handwritten text recognition system.[3] This research focuses on developing a framework that integrates these technologies—OCR, clinical NLP, and machine learning—to transform both handwritten and digital PSLOV clinical notes into structured data. The structured outputs are then used to train predictive models using algorithms such as Random Forest, XGBoost, and Support Vector Machine to classify the underlying cause of vision loss (e.g., CRAO, CRVO). These models help in automating early diagnosis and improving clinical workflow.[4,5] From an information technology research perspective, this work aims to demonstrate how unstructured clinical documentation can be systematically digitized, structured, and analyzed to support data-driven healthcare decisions. The outcome contributes to both technological innovation and clinical utility by unlocking the predictive value hidden in routine medical texts. This problem becomes increasingly important when considering Painless Sudden Loss of Vision (PSLOV), a clinical scenario that encompasses potentially blinding ophthalmic diseases such as Central Retinal Artery Occlusion (CRAO), Central Retinal Vein Occlusion (CRVO), Branch Retinal Artery Occlusion (BRAO) and Branch Retinal Vein Occlusion (BRVO). To narrow this difference between unstructured clinical narratives and organized, machine-readable data artificial intelligence solutions have arisen, particularly in the field of clinical Natural Language Processing".

This problem becomes increasingly important when considering Painless Sudden Loss of Vision (PSLOV), a clinical scenario that encompasses potentially blinding ophthalmic diseases such as Central Retinal Artery Occlusion (CRAO), Central Retinal Vein Occlusion (CRVO), Branch Retinal Artery Occlusion (BRAO) and Branch Retinal Vein Occlusion (BRVO).[6] Some Meaningful parameters in disease diagnosis including symptoms, chronology, anatomical details, and diagnoses can be extracted from clinical writings and transformed into structured data components by using natural language processing (NLP) approaches.[7,8]

An observational study on vitreous hemorrhage at the Tilganga Institute of Ophthalmology in Kathmandu found that most cases presented unilaterally, that individuals between the ages of 51 and 60 were more likely to be affected, and that there was a significant male predominance (144 vs. 54). In 95 % of patients, the initial complaint was sudden eyesight loss.[9] The most frequent cause (22,38 %) was found to be branch retinal vein blockage, which was closely followed by proliferative diabetic retinopathy, vasculitis, trauma, and retinal detachment. Most common comorbidities were diabetes and systemic hypertension. The majority of treatment was medical (57,7 %); 35,8 % required surgery, and 6,47 % had both medical and surgical treatments. According to Math, C. sudden vision loss is a medical emergency with a wide range of potential causes, such as inflammation, nerve disorders, and vascular obstructions.[10] The study emphasizes how important it is to differentiate between painful and painless vision loss when choosing a course of treatment. With an emphasis on early detection and treatments to preserve vision, conditions such vitreous hemorrhage, optic neuritis, retinal artery occlusion, and retinal vein occlusion are covered. In order to detect underlying risk factors and prevent recurring ocular or systemic occurrences, the work emphasizes the need of systemic assessment and the need for prompt ophthalmologic evaluation.

The causes, detection methods, and treatment developments of retinal vein occlusion (RVO) are reviewed by Lendzioszek et al.[11] Common health issues like diabetes, high blood pressure, high cholesterol raise risk, eye disorders like glaucoma can exacerbate it. Newer imaging techniques, including OCT and OCT angiography, are highlighted in the research as aiding in the more precise diagnosis of RVO and the monitoring of its consequences, particularly macular edema. Along with their drawbacks, like the requirement for repeated treatments, current therapies, primarily anti-VEGF injections and steroid implants, are examined. In summary, the article combines foundational knowledge with fresh insights to assist clinicians and researchers in tackling this sight- threatening disorder.

Berguig et al.[12] conducted a study on young individuals under 40 years and who are diagnosed with CRVO. It identified the associated risk factors and assess visual outcomes of the patients and found that Central Retinal Vein Occlusion (CRVO) is a common retinal vascular disorder with a prevalence of 0,8 per 1000 people, typically affecting older adults due to risk factors like hypertension, glaucoma, and systemic inflammation. However, 10–15 % of CRVO cases occur in individuals under 40. This Paper reveals that the Central Retinal Vein Occlusion (CRVO) is less prevalent in young patients than in older populations, presents distinct risk factors and clinical considerations. Different text parsing algorithms have been used in analyzing the clinical data. Semantic text parsing techniques have been used in extracting clinical data using regular pattern recognition.[13] Utilization of regular expression in pattern matching is being done in scalable architecture for high throughput.[14] In implementing regular expression pattern matching algorithms, researchers have used the concatenation, base index creation, and solution graph creation methods.[15] The concept of creating Parsed Expression Grammar (PEG) for recognizing patterns in a given input paragraph has been implemented by the researchers. Similar algorithms have been used in pattern recognition of different languages.[16]

Different text parsing algorithms have been used in analyzing the clinical data. While classical machine learning algorithms perform well in classifying a dataset, use of ensemble techniques i.e. combining different machine learning algorithms perform better than the standalone algorithms.[17] Lee et al. used machine learning to predict the etiology of fundus- obscuring vitreous hemorrhage (VH. The author used clinical variables, ocular findings, and imaging data, multiple algorithms like random forest and gradient boosting. The models differentiated common causes such as retinal vein occlusion, retinal tears, and proliferative diabetic retinopathy, and achieved high diagnostic performance of AUC > 0,85.[18] XGBoost DART enhances the powerful gradient boosting framework by incorporating dropout, a form of regularization that reduces over-specialization and overfitting. For a structured dataset on painless sudden vision loss where data is precious, patterns are complex, and prediction accuracy is critical, DART offers a robust path to a high-performance diagnostic model.[19] Its ability to learn complex feature interactions while mitigating the risk of overfitting makes it a top choice for such a clinical prediction task. The key to success lies in rigorous hyperparameter tuning and a disciplined train/validation/test split to ensure the model's generalizability to new, unseen patients.[20] Chen and Baxter provided a comprehensive review of NLP applications in ophthalmology where the research discussed both current practices and future directions.[21] The structured data from electronic health records (EHRs) have been extensively utilized, and the unstructured free-text data such as clinical notes are under utilized. Early NLP were focused on extracting specific information like visual acuity and intraocular pressure from clinical notes. These used rule-based methods. More recent advancements involve machine learning techniques. These include word embeddings and transformer models to enhance data extraction and predictive modeling. The authors suggest that NLP can be used for search engines for clinical notes, automated question-answering, and translation tools for ophthalmology notes. These innovations may improve clinical decision-making and patient care in ophthalmology.

METHOD

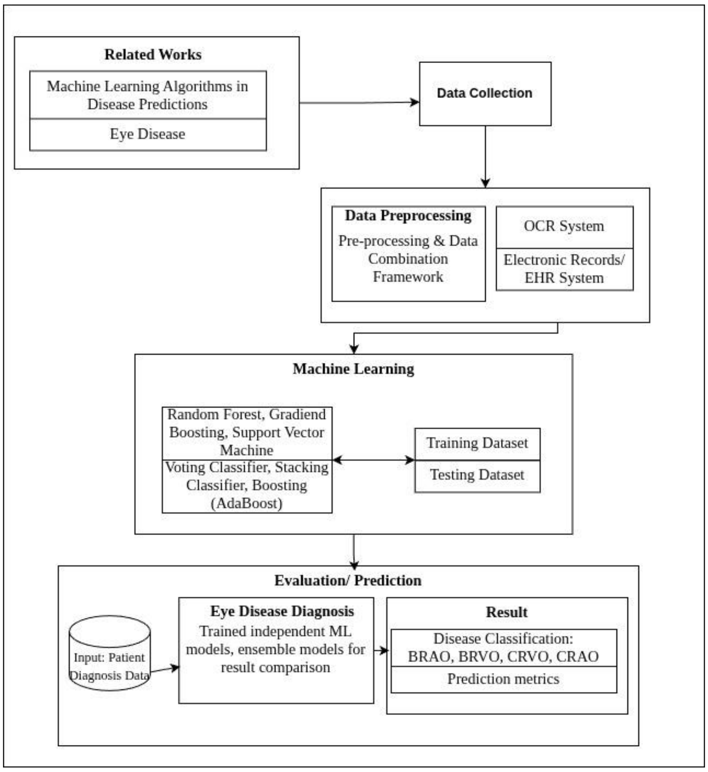

Figure 1. Research Framework

This research involves developing a data aggregation framework which inputs data from the OCR System and electronic records from the EHR system shown in figure 1.

Data collection

Data is retrieved from two sources, an OCR System and Electronic records from EHR systems of different hospitals. The OCR System we developed is an integrated system which uses Bidirectional Long Short-Term Memory networks (BLSTM) and Convolutional Neural Networks (CNN) to convert doctor handwritten text prescriptions to digital data.(1) Electronic records of eye diseases were retrieved from EHR softwares used in Dristi Eye Hospital. Ethical consideration and permission to access patient information was taken from respective institutions. The data provided from the hospital had the patient's personal information blinded. Only disease, symptoms, history, diagnosis were retrieved from EHR systems. From the OCR system we were able to parse the patients' medical records using machine learning algorithms and convert the prescriptions in json format.(21) We developed a dataset which has a total of 28 input parameters and one target feature. Dataset has information of the following category: age, gender, History: diabetes mellitus type 2, carotid artery, hyperlipidemia, hypertension, glaucoma, myopia, ocular refractive surgery, Vision: Sudden blurring, sudden loss, flashes, floaters, pain, redness, Trauma, Visual acuity, pupils, fundoscopy, IOP, OCT, other relevant history, aggravating factors, relieving factors, family history, and USG and the target feature is diagnosis. The target feature had four classes CRAO, CRVO, BRVO, and BRAO. Both of these data were further mapped and merged. Details are highlighted in the preprocessing step.

Preprocessing

We developed a data preprocessing pipeline to handle the data input from OCR System as well as the EHR System. The preprocessing first includes the json to csv conversion of the lines of prescription which were extracted as a part of the OCR System.(22) OCR System uses BLSTM and CNN algorithms to analyze the doctor's handwritten prescription to parse JSON files. The text-to-csv parameter extraction pipeline shown in Fig. 02 is developed to convert the JSON file to CSV. The EHR systems of each hospital records patient data electronically.

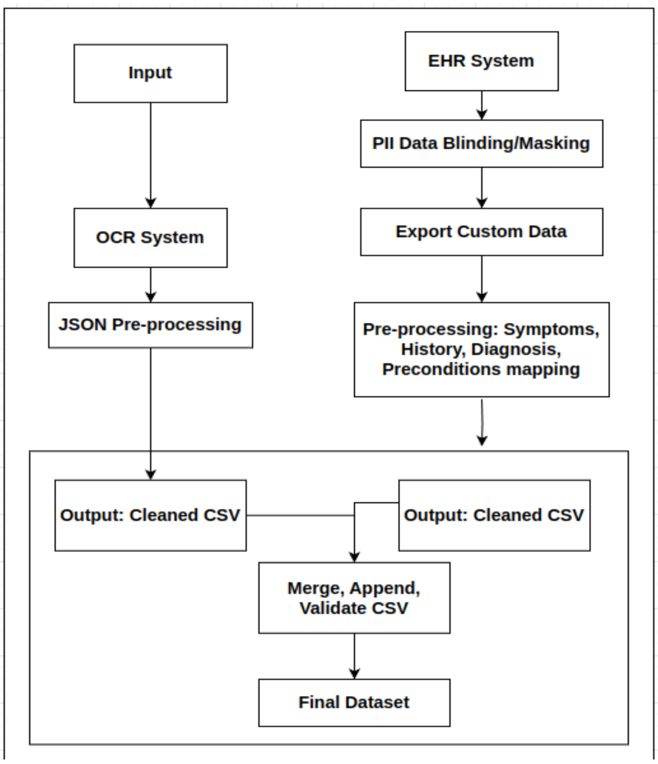

Figure 2. Data Preprocessing Pipeline

After official permission from each hospital, the hospital provided us digital records removing patient personal identification information. We then combined the data from both data sources, mapped and merged it for data preprocessing.

Symptoms, History, Diagnosis Mapping

The EHR digital records initially had twenty eight features related to eye disease. After rigorous study of literature five different parameters were removed from the dataset for further processing.(23) A data pipeline

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was developed to pre-process the final dataset of 24 parameters (Input and target features). Its architecture is shown in figure 3.

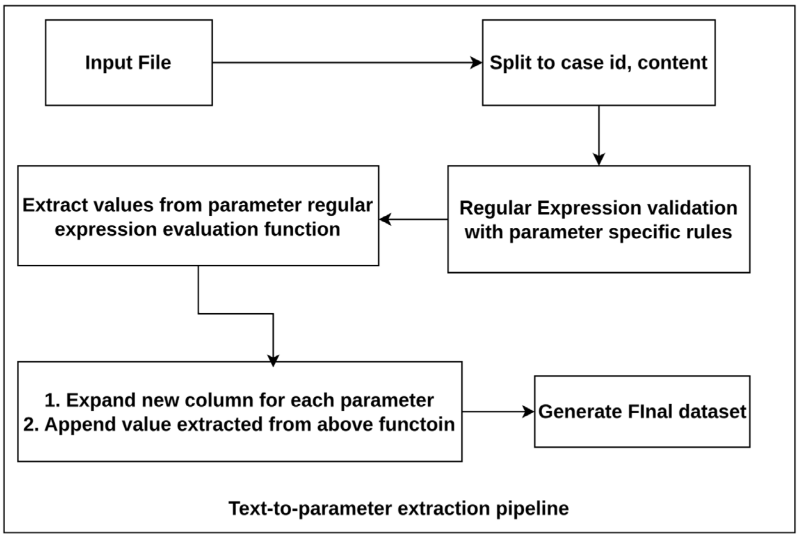

Figure 3. Text-to-parameter extraction Pipeline

Exploratory Data Analysis

Data from EHR and OCR systems had some missing values. To handle such cases we used strategies like filling standard values 20/6 to feature visual acuity of both left and right eye. Some entries of data didn't have its target variables. We removed those entries since the target variable is necessary for the analysis.

OCR and EHR Data Field Mapping

For a single patient's medical prescription the OCR system did image to text analysis. And from the same patient we collected their digital record from the EHR system. We did a simple map and reduce task which compared the fields received from the EHR and OCR system. For null records in any source the empty record was assigned as N. If any input source had additional fields, they were discarded, reducing to a total of twenty four features.

Feature Extraction

This step includes identification of the target feature to evaluate the results of the machine learning analysis. We performed a blend of literature review and python programming to associate the symptoms, history, diagnosis and preconditions with the target feature. Target feature is a multi-class classification variable having five diseases for prediction, CVRO, BRAO, BRVO, and CRAO. Our research is a multiclass classification problem dealing with different types of diseases. These features will be used in developing models and training for prediction.

Training

The model has been trained for classifying association of symptoms, history, diagnosis, and preconditions with target features i.e. eye diseases. Being a multiclass classification problem we have used two machine learning algorithms Support Vector Machine, and Random Forest Classifier. The dataset is trained over these two algorithms over the input data keeping an weightage of the train:test as 80:20 [Y]. No annotation was required as we used the json file to parse them to CSV. We then applied ensemble techniques to improve the accuracy by combining the machine learning models. XGBoost Dart was used to train the data. The results are displayed in the next section.

Experiment

This section covers the experimental environment used to run the data analysis, performance evaluation measures used to calculate the classification accuracy in detail.

Performance Evaluation

ROC curve analysis is performed across algorithms for all four target classes which is shown in figure 4.

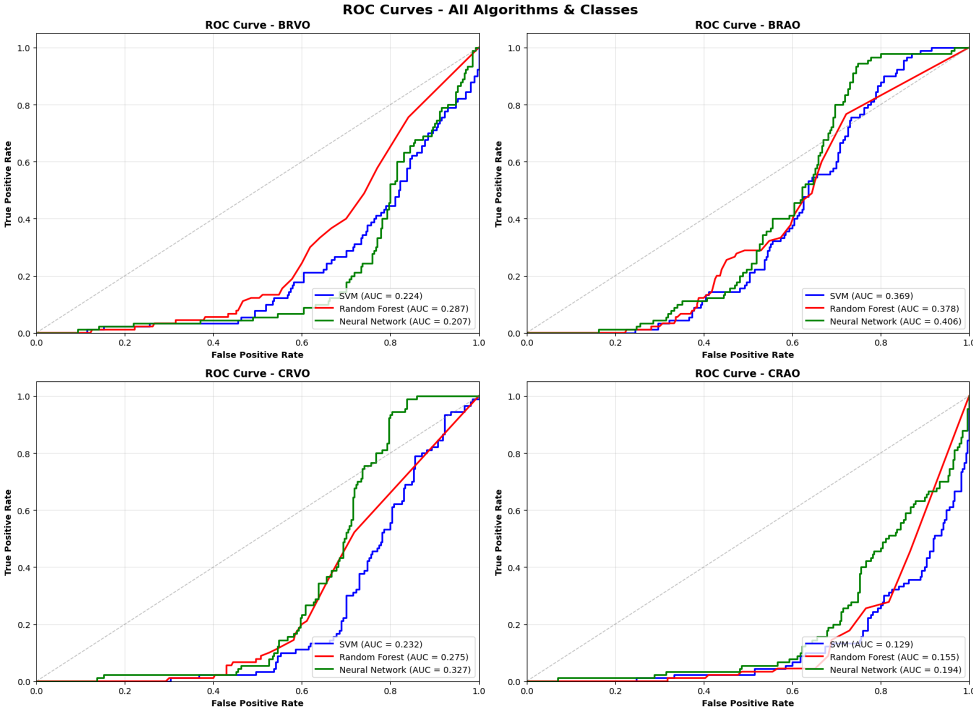

Figure 4. ROC Analysis of target features across all algorithms

Figure above highlights the results over each target classes where SVM has a micro AUC of 0,9605 and macro AUC of 0,2384, Random Forest has Macro AUC of 0,2736 and Micro AUC of 0,9579, Neural Network has Micro AUC of 0,9466

RESULTS

Table 1 shows the result of classification analysis of the training data with the machine learning models Neural Network, SVM, Random Forest for the experimentation:

Table 1. Classification Analysis Results

Evaluation Metrics	Random Forest	SVM	Neural Network	Target Class
f1-score	0,78	0,86	0,89	BRAO
precision	0,79	0,88	0,90	
recall	0,78	0,86	0,89	
accuracy	0,85	0,89	0,92	
f1-score	0,73	0,88	0,90	BRVO
precision	0,74	0,89	0,92	
recall	0,78	0,88	0,89	
accuracy	0,84	0,89	0,9375	
f1-score	0,72	0,88	0,93	CRAO
precision	0,76	0,89	0,93	
recall	0,76	0,88	0,93	
accuracy	0,85	0,89	0,91	
f1-score	0,72	0,87	0,92	CRVO
precision	0,74	0,89	0,92	
recall	0,72	0,86	0,93	
accuracy	0,84	0,90	0,91	

Further the dataset was trained using the variant of XGBoost to improve the generalization and inspired by dropout in neural networks as XGBoost DART [20]. Here the objective function balances the prediction accuracy with model complexity during the training process:

$L(\theta) = \Sigma(i=1 \text{ to } n)\ l(yi, \hat{y}i) + \Sigma(k=1 \text{ to } K)\ \Omega(fk)$ (1)

Where:
$l(yi, \hat{y}i)$ is the loss function between true label yi and prediction $\hat{y}i$.
$\Omega(fk)$ is the regularization term for the k-th tree.
K is the total number of trees.

Speciality about XGBoost DART is its ability to meet adaptive regression. Meaning only a subset of trees (Kt) contribute to the prediction process. DART formula is given below:

$\hat{y}i^\wedge(t) = \hat{y}i^{t-1} + \eta\ \Sigma(k \in Kt)\ fk(xi)$ (2)

Where:
Kt is the set of trees selected (not dropped)at iteration t.
η is the learning rate.
Dropout probability p determines which trees to drop.

XGBoost DART performs multi-class classification by converting raw tree outputs into probabilities using softmax where all four target features BRVO, BRAO, CRVO, CRAO achieves its ensemble prediction Fc(x) given in equation 3.

$P(y = c|x) = e^{Fc(x)} / \Sigma(j=1 \text{ to } 4)\ e^{Fj(x)}$ (3)

Where: **Fc(x)** is the ensemble prediction for target classes. Table 2 below displays the overall training accuracy result of XGBoost DART.

Table 2. Classification accuracy of Test Data using XGBoost DART

Algorithm	Accuracy	Precision	Recall	F1-Score
XGBoost DART	0,9401	0,84	0,84	0,84

Accuracy, precision, recall, and F1-Score achieved were 0,9401, 0,84. 0,84, and 0,84 respectively. XGBoost Dart showed improved results compared to Random Forest, SVM, and Neural Network. Table 3. shows the classification accuracy result of multi-class classification using XGBoost DART. Accuracy, precision, recall, and F1-Score of individual target features BRVO, BRAO, CRVO, CRAO are listed below.

Table 3. Classification accuracy result over all target features

	Accuracy	Precision	Recall	F1-Score
BRVO	0,9391	0,8222	0,8222	0,8222
BRAO	0,9537	0,8706	0,8222	0,8457
CRVO	0,9299	0,845	0,845	0,845
CRAO	0,9377	0,8842	0,9333	0,9081

Table 4 shows the comparison between classification accuracy of using SVM, Random Forest, Neural Network, and XGBoost DART algorithms.

Table 4. Evaluation Metrics Comparison

Algorithm	Accuracy	Precision	Recall	F1-Score	AUC
SVM	0,892	0,8263	0,8250	0,8244	0,9609
Random Forest	0,845	0,7984	0,7972	0,7968	0,9572
Neural Network	0,919	0,8082	0,8083	0,8078	0,9462
XGBoost DART	0,9401	0,8443	0,8444	0,8440	0,9650

The final evaluation result shown in table 4. highlights the comparison of evaluation metrics over SVM, Random Forest, Neural Network, and XGBoost Dart with accuracy of 0,892, 0,845, 0,919, and 0,9401 respectively.

CONCLUSIONS

Random forest yielded the least accuracy of 84,5 % and XGBoost DART with 94,01 %. XGBoost DART being a specialized form of gradient boosting algorithm performed the best with the available dataset of our research. The machine learning model we built successfully predicted the test data with an average of 89,9 %. As a part of future work, this research work can be extended by experimenting with extra machine learning models. We can increase the dataset of disease, diagnosis and medicines getting more accurate results. An area of improvement for this research would be to minimize the losses in the classification accuracy.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

AUTHORSHIP CONTRIBUTION

Conceptualization: Santosh Khanal, Rabindra Bista.
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Formal analysis: Santosh Khanal.
Research: Santosh Khanal.
Methodology: Santosh Khanal.
Project management: Santosh Khanal, Rabindra Bista.
Resources: Santosh Khanal.
Software: Santosh Khanal.
Supervision: Rabindra Bista
Validation: Santosh Khanal, Rabindra Bista.
Display: Santosh Khanal.
Drafting - original draft: Santosh Khanal.
Writing - proofreading and editing: Santosh Khanal, Rabindra Bista.