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An auxiliary role of deep neural network ophthalmic disease identification models in choosing medication treatment strategy

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Abstract: To evaluated a Deep Neural Network (DNN)-based ophthalmic disease diagnosis framework in facilitating personalized medication treatment plans using a prospective, single-center, randomized controlled clinical trial design. 500 patients were randomly assigned to either a DNN-aided experimental group or a control group receiving standard physician-based treatment plans. The primary outcomes were medication selection accuracy, clinical efficacy (assessed by BCVA and CMT), patient compliance, and adverse reaction management. Results showed that DNN-aided treatment plans significantly improved medication selection accuracy and treatment quality, with higher BCVA and CMT scores in the experimental group. Patients in the experimental group also demonstrated higher compliance and a trend towards lower adverse reaction rates. The study highlights the potential of DNN models to enhance ophthalmic disease management, offering precise and personalized treatment strategies with potential benefits for patient outcomes and safety as AI technology advances.

Keywords: AI; DNN; Ophthalmic diseases; personalized medicine; clinical study; medication compliance; side effects

INTRODUCTION

Ophthalmic diseases are among the leading causes of vision loss and decreased quality of life worldwide. Chronic conditions such as glaucoma, diabetic retinopathy, and age-related macular degeneration (AMD) have seen a significant increase in incidence in recent years, imposing a considerable burden on public health systems (Li *et al*., 2022, Hodges *et al*., 2024, Li *et al*., 2022). With the rapid development of artificial intelligence (AI) technologies, deep neural networks (DNNs) have shown substantial promise in medical image processing, particularly in the screening and diagnosis of ophthalmic diseases, where they have demonstrated remarkable results (J Yang *et al*., 2021, Gurnani *et al*., 2024). For example, deep learning-based algorithms can effectively identify disease features from retinal images, reducing diagnostic errors and time (Zhang *et al*., 2021). However, in modern clinical practice, these models primarily focus on disease identification and diagnosis. Expanding their application beyond diagnostic tasks, particularly in medication treatment decision-making, remains a critical area for further research (Galderisi *et al*., 2024).

Medications are crucial in managing ophthalmic diseases, with treatment strategies typically based on the nature and severity of the condition as well as the clinician's expertise (Phu *et al*., 2021). In complex diseases like wet AMD, physicians must integrate the patient's medical history, imaging data, and pathophysiological changes to develop personalized anti-vascular endothelial growth factor (anti-VEGF) treatment plans (Adamis *et al*., 2020, (Santorsola *et al*., 2024, Gacche, 2020). However, due to differences in disease progression and the variability between patients, the conventional approach to formulating treatment plans is often time-consuming and somewhat subjective. This can result in variability in therapeutic outcomes. Therefore, the need to leverage DNNs to integrate multimodal data and improve the precision and scientific nature of treatment planning is an area that cannot be overlooked.

Recently, there has been a growing interest in using deep learning technology to support treatment decision-making systems for ophthalmic diseases. For instance, some studies have used DNNs to analyze imaging and pathological indicators to predict the effectiveness of anti-VEGF therapy, providing valuable decision support for physicians (Wong *et al*., 2021, Tabuchi *et al*., 2023). The ability of deep neural networks to process complex, high-dimensional inputs allows them to simultaneously handle diverse information, including OCT images, retinal photographs, and genetic data, facilitating improved disease diagnosis and personalized treatment recommendations for patients. These advances suggest that applying deep learning models in ophthalmic drug treatment selection has significant potential.

Despite these promising advancements, there are several limitations that hinder the broader use of DNNs in clinical settings. Firstly, the "black box" nature of deep learning models makes their decision-making processes difficult to interpret, leading to a lack of trust in their predictions among clinical practitioners (Khan *et al*., 2024). Secondly, the data used to train these models often exhibit significant heterogeneity across different medical institutions, and the sample sizes may be insufficient to develop robust and generalized models. Furthermore, integrating model outputs into clinical workflows remains an open challenge. Therefore, developing DNN-based models for ophthalmic disease diagnosis and drug treatment recommendations

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requires not only technical advancements but also careful consideration of clinical relevance and ethical implications.

This research aims to develop a deep neural network-based disease detection and drug treatment recommendation system, using wet AMD as a case study, to explore the auxiliary role of such a model in medication selection. Specifically, this study integrates deep learning models, OCT images, clinical indicators, and treatment feedback data to identify disease characteristics as accurately as possible and predict the therapeutic outcomes of anti-VEGF drugs. A comprehensive evaluation of the model's performance will assess whether it can effectively optimize the treatment decision-making process, enhancing treatment efficacy and precision. Additionally, this research will address the practical challenges of applying such a model in the clinical healthcare setting. The insights gained from this study will not only further the application of AI technology in ophthalmology but also serve as a paradigm for managing other chronic diseases.

MATERIALS AND METHODS

Study design

This work used a prospective, single-center, randomized clinical trial approach. The target population comprised new patients to our hospital's ophthalmology department from January 2019 to December 2023 who fulfilled the inclusion criteria. Once the ophthalmic disease recognition model provided risks about patients, treatment decisions were made according to the model's suggestions.

In the present study, aimed to assess the DNN-based ophthalmic disease recognition model to help choose drug treatment and compare the results with traditionally chosen drugs. The participants received informed consent and were divided into an experimental group (compared with those treated by traditional treatment) and a control group (using a model-assisted treatment). The treatment course designed for the experimental group was based on the model predicted from the clinical information and images, while the control group relied on the clinician's qualitative opinion and experience.

Study population

Inclusion Criteria: Top recruiting criteria include: (1) Candidates must be 18 to 75. Diseased with usual ophthalmic disease, including age-related macular degeneration (AMD), diabetic retinopathy (DR), glaucoma, or optic neuropathy. Access to one; (3) Capacity to read and sign the informed consent form. It does the following: (4,4) No severe hepatic or renal impairment, major disease history, infectious diseases, or other serious chronic illnesses.

Exclusion Criteria: Eye surgery in the past or receiving recent eye surgery. Cardiovascular, neurological, immune system diseases or other severe conditions impact treatment - serious condition two pregnant or breastfeeding women Pregnant or breastfeeding women Patient who did not provide follow-up or cannot complete the trial in any way.

Data Collection

These sources included the participants' demographic characteristics such as age, sex, medical history, and clinical findings, which included but were not limited to the visual acuity, intraocular pressure fundus photographs, OCT, fluorescein angiography, laboratory investigations including blood glucose level, lipid profile, blood pressure, treatment plan, and outcome. The nurses and the physicians collected the data to ensure quality data was collected through data triangulation and reliability.

4. The process of constructing a deep neural network model

Data preprocessing

Some of the collected data in the form of fundus images, OCT scans and clinical records were analyzed and cleaned up. All images were standardized, with image data being augmented for increased variation, and all clinical data, including age and patient history, were normalized for input to the model.

Model architecture

A deep neural network (DNN) was employed in the form of a convolutional neural network (CNN) for the modeling of ophthalmic images. The model had several layers of convolution, pooling, and fully connected layers, plus an output layer in the form of a SoftMax layer to form the classification. The output was, therefore, in the form of a prediction of the disease type and an appropriate treatment regimen.

The other model training and optimization

The training data consisted of imaging and clinical data from 2,000 patients in our hospital. Correspondingly, the dataset was randomly split into training and validation sets. The model was trained for 50 epochs using the cross-entropy loss and Adam optimizer and an initial learning rate of 0.001. Included were accuracy, sensitivity, specificity, F1 score, and area under the curve (AUC).

Model validation

To test for overfitting, 10-fold cross-validation was applied. The overall dataset was split into 10 partitions: the first nine were used for training and the last for testing. Performance for one is independent averages to determine the stability of the model.

Drug treatment plan selection

The experimental group selected treatment plans based on the model's outputs using the following steps: Model Output Analysis: Using the captured imaging (for instance, OCT scans, fundus photographic images) and clinical history, the model identified the most appropriate

ophthalmic disease type. (2) Drug Recommendation: According to the identified disease, the model suggested suitable drugs- either local agents- anti-VEGF drugs, or systemic agents- antidiabetic drugs, ocular hypotensive drugs. It was established that drug type and dosage depend on patient conditions. (3) Treatment Adjustment: Based on treatment success and side effects, the model offered new suggestions depending on therapeutic advancement and imaging alterations.

In the control group, drug selections were based on the clinician's experience and standard protocols. Complication control for treatment success with side effects was managed with ophthalmic examination and imaging reports.

Efficacy evaluation

The following measures were used to evaluate treatment efficacy: Visual acuity LogMAR visual acuity was also measured in the patients before they received treatment, one month after, and three months after. (2) Fundus Changes: Fundus pictures and optical coherence tomography were used to evaluate the macular shape and the thickness of the optic nerve head. (3) Central Macular Thickness (CMT): The changes evident in CMT were assessed using OCT and tested for statistical differences in the subgroups. (4) Adverse Events: Drug safety was determined by the adverse effects and clinical examination done during the study period. Details were recorded within three months before and after treatment, and two ophthalmologists examined the data.

STATISTICAL ANALYSIS

All statistical indexes were computed using SPSS 25.0 statistics. Data were presented as mean ± standard deviation (Mean ± SD), and for differences between groups, t-tests were used. A Chi-square test was employed to assess categorical variables. Multiple regression analysis was also performed to review the internalization patterns determining the treatment choice and response. The level of statistical significance taken in the study was 0.05.

Ethical Considerations

Therefore, this work meets the Declaration of Helsinki standards and conventional ethical requirements. Informed consent was the subject of the study, and all patients agreed to participate in the project. The study was conducted in compliance with the requirements of the hospital ethics commission, which had the number 2023-EY-001.

RESULTS

Baseline characteristics analysis

A total of 500 patients were enrolled in this study, with 250 in the experimental group receiving deep neural network (DNN)-assisted medication treatment plan selection, and 250 in the control group receiving traditional physician-subjective judgment medication treatment plans. There were no statistically significant differences in gender, age, medical history, and basic clinical indicators between the two groups ($P>0.05$), indicating that the baseline characteristics of the two groups were similar at the time of enrollment, allowing for comparative analysis. Specific baseline characteristics are shown in table 1.

Imaging data and clinical indicators analysis

In terms of imaging assessments, the fundus photographs, OCT scans, and fluorescein angiography of patients in the experimental group showed a significant reduction in macular thickness after using the DNN-assisted treatment plan. Specifically, the central macular thickness (CMT) in the experimental group decreased by 15.3% ($P<0.001$) three months after treatment, while the control group only showed a 6.4% reduction ($P<0.05$). OCT revealed that the improvement in the macular area and retinal nerve fiber layer thickness in the experimental group was significantly better than in the control group. table 2 presents the OCT macular thickness and optic nerve head thickness before and after treatment.

Visual acuity changes

Based on the changes in Best Corrected Visual Acuity (BCVA), there was also a significant difference in visual improvement between the experimental and control groups after treatment. Three months after treatment, the BCVA of patients in the experimental group significantly improved, with an average improvement of 0.12 ± 0.08 ($P < 0.001$), while the vision of patients in the control group only improved by 0.04 ± 0.05 ($P = 0.03$). Sixty-five percent of patients in the experimental group had an improvement in vision exceeding 0.1 Snellen acuity units, significantly higher than the 45% in the control group. These results indicate that the DNN-assisted medication treatment plan is superior to traditional treatment methods in improving vision.

Medication selection and treatment adherence

In terms of medication selection, the medication treatment plans for patients in the experimental group were more in line with the latest clinical guidelines and standard treatment protocols, while the control group relied more on the clinical experience of physicians. In the experimental group, the DNN-assisted recommendation provided precise medication selection, and the medication treatment adherence was high, with 89% of patients taking medication on time and following medication adjustment plans; in the control group, only 76% of patients could adhere to the treatment plan. Statistical analysis of treatment adherence differences showed that the treatment adherence in the experimental group was significantly higher than in the control group ($P < 0.05$).

Adverse reaction analysis

The incidence of adverse reactions during treatment was monitored. The proportion of patients in the experimental

Table 1: Baseline characteristics of participants in the experimental and control groups

Characteristic	Experimental Group (n=250)	Control Group (n=250)	P-value
Gender (M/F)	130/120	128/122	0.832
Age (years)	65.2 ± 9.3	64.8 ± 9.5	0.704
Diabetes History	98 (39.2%)	102 (40.8%)	0.803
Hypertension History	120 (48%)	118 (47.2%)	0.878
Retinal Disease History	45 (18%)	42 (16.8%)	0.772
Fundus Lesion	65 (26%)	68 (27.2%)	0.813

Table 2: Comparison of OCT macular thickness and change percentages before and after treatment

Group	Pre-treatment CMT (μm)	Post-treatment CMT (μm)	Change Percentage (%)	P-value
Experimental Group	314.5 ± 25.3	266.3 ± 21.7	-15.3%	<0.001
Control Group	316.2 ± 26.1	296.4 ± 22.3	-6.4%	0.032

Table 3: Incidence of adverse reactions in the experimental and control groups

Group	Pre-treatment BCVA (Snellen units)	Post-treatment BCVA (Snellen units)	Change (Snellen units)	P-value
Experimental Group	0.32 ± 0.16	0.44 ± 0.18	0.12 ± 0.08	<0.001
Control Group	0.33 ± 0.15	0.37 ± 0.14	0.04 ± 0.05	0.030

group who experienced adverse reactions was 6.8% (17/250), mainly manifested as mild ocular irritation symptoms and local allergic reactions. The incidence of adverse reactions in the control group was 9.6% (24/250), mainly related to drug-induced intraocular pressure elevation and retinal bleeding. There was no statistically significant difference in the incidence of adverse reactions between the two groups (P = 0.188). Table 3 summarizes the types of adverse reactions in both groups.

Table 4: Best Corrected Visual Acuity (BCVA) changes before and after treatment

Group	Treatment Adherence (%)	P-value
Experimental Group	89	<0.05
Control Group	76	

Clinical efficacy assessment

According to the clinical efficacy criteria (improvement, stability, deterioration), 82% of patients in the experimental group showed improvement in symptoms after treatment, 15% had stable conditions, and only 3% deteriorated. In contrast, only 62% of patients in the control group showed improvement, 25% were stable, and 13% deteriorated. The differences were statistically significant (P<0.001).

Deep neural network model performance

In terms of deep neural network model performance evaluation, the model's accuracy was 92.5%, sensitivity was 90.7%, specificity was 94.1% and AUC was 0.95. This indicates that the deep neural network-based ophthalmic disease identification model has high accuracy in diagnosing ophthalmic diseases and recommending medication treatment plans.

DISCUSSION

In recent years, the rapid advancement of artificial intelligence (AI) in science and technology has led to the widespread application of deep neural networks (DNNs) in the medical field, particularly in the diagnosis of ophthalmic diseases and the formulation of treatment plans. This study aimed to evaluate the efficacy of a DNN-based ophthalmic disease identification model in guiding medication treatment decisions, comparing its outcomes with traditional physician-led approaches. The findings demonstrate that DNN-based treatment recommendations not only enhance the accuracy of medication selection but also improve clinical treatment outcomes and patient adherence to prescribed regimens. Below, we elaborate on several key aspects of these findings.

Benefits of the DNN-based ophthalmic disease identification model

The study highlights the effectiveness of DNN-based frameworks in diagnosing ophthalmic diseases and assigning appropriate medication regimens. By leveraging DNN technology, large volumes of complex medical data—including fundus photographs, optical coherence tomography (OCT) images, and fundus fluorescein angiography—can be rapidly preprocessed and analyzed to extract critical features from medical images (S Lee *et al*., 2022). This automated process eliminates human bias, thereby improving the accuracy of treatment selection.

Traditional approaches to ophthalmic disease treatment often rely on physicians' clinical experience and data from clinical trials (Terpos *et al*., 2021, Zöller *et al*., 2024).

Table 5: Medication treatment adherence in the experimental and control groups

Adverse Reaction Type	Experimental Group (n=250)	Control Group (n=250)	P-value
Ocular Irritation	7 (2.8%)	9 (3.6%)	0.672
Local Allergic Reaction	6 (2.4%)	8 (3.2%)	0.775
Intraocular Pressure Elevation	3 (1.2%)	10 (4%)	0.043
Retinal Bleeding	1 (0.4%)	4 (1.6%)	0.152

Table 6: Clinical efficacy assessment of treatment outcomes in the experimental and control groups

Group	Improvement (%)	Stability (%)	Deterioration (%)	P-value
Experimental Group	82	15	3	<0.001
Control Group	62	25	13	

However, the subjective nature of physician judgment, coupled with individual variations in disease presentation, can lead to suboptimal treatment decisions. In contrast, DNN models, trained on extensive datasets from past cases, can not only identify specific ophthalmic diseases but also predict treatment outcomes and tailor therapies to individual patients. For instance, this study found that patients treated using DNN-based medication plans exhibited reduced macular thickness and better visual outcomes compared to those treated with traditional methods (Sorrentino *et al*., 2024).

Table 7: Performance metrics of the deep neural network model

Performance Metric	Value
Accuracy	92.5%
Sensitivity	90.7%
Specificity	94.1%
AUC	0.95

Enhanced clinical treatment outcomes

The integration of DNN into clinical practice led to a 15% improvement in treatment efficacy in the experimental group compared to the control group. Patients in the experimental group showed significant gains in visual acuity and reductions in macular thickness over a three-month period. These findings align with prior research, further validating the utility of DNN technology in ophthalmic disease treatment. For example, Chong *et al*. (2022) demonstrated that AI-assisted treatment plans improved vision in patients with diabetic retinopathy (Elmarakeby *et al*., 2021, Tran *et al*., 2021). In this study, the experimental group exhibited a mean improvement in best-corrected visual acuity (BCVA) of 0.12±0.08, compared to 0.04 ± 0.05 in the control group. These results underscore the potential of DNN-based treatment plans to enhance patient vision, prevent the progression of fundus lesions, and improve quality of life.

Improved treatment adherence

Treatment adherence, a critical factor in therapeutic success, was significantly higher in the experimental group (89%) than in the control group (76%). This improvement can be attributed to the DNN model's ability to provide patients with precise and personalized treatment information, thereby reducing uncertainty and enhancing trust in the therapeutic process. Other studies have similarly highlighted the role of AI in boosting patient compliance through optimized treatment plans and medication selection (Maglidt, 2023, Ezeamii *et al*., 2024, Rosário and Rosário, 2024).

Control of adverse reactions

The experimental group experienced a lower incidence of adverse reactions (6.8%) compared to the control group (9.6%). This reduction suggests that DNN-based treatment plans can minimize side effects by optimizing medication dosages and combinations. In ophthalmic treatment, where adverse reactions are a common concern, DNN models can integrate patient characteristics, medical histories, and drug interactions to guide safer and more effective treatment decisions. Previous research also supports the capability of AI models to predict and mitigate adverse drug reactions (Yang, 2022).

Limitations and future directions

While this study underscores the potential of DNN-based models in ophthalmic disease treatment, certain limitations must be acknowledged. First, external factors such as patients' psychological states and lifestyles may influence treatment outcomes. Future research should expand sample sizes and incorporate broader social and psychological variables. Second, while DNN models excel in disease identification and medication selection, further refinement of algorithms and model generalization is essential. Given the reliance of DNN models on extensive clinical datasets, hospitals and research institutions must provide diverse and system-level data to enhance model adaptability. Future studies should also explore the validation and tuning of models across different hospitals, regions, and injury types (Z Su *et al*., 2024, K Uma *et al*., 2023). Finally, while DNN models offer valuable recommendations, they cannot replace clinical judgment. Future research should focus on integrating AI with physicians' expertise to develop a "physician-computer hybrid" treatment model, ensuring superior therapeutic outcomes. By addressing these limitations, DNN-based ophthalmic disease identification

models hold significant promise for advancing personalized medicine and improving patient care.

CONCLUSION

The use of DNN-based ophthalmic disease identification models in selecting medication treatment plans can greatly improve the selection methods of medication accuracy, promote the optimization of patient treatment, improve patient compliance, and prevent and reduce adverse reactions. Despite some obvious drawbacks, the possibilities of its application in treating ophthalmic diseases are rather vast. In the future, as AI innovation advancements become more significant, deep neural networks will assume an even more significant role in clinical management and will present new ideas and approaches to treating ophthalmic diseases.

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