Transformer-Based Machine Learning for Glaucoma in Nepal

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Abstract

Glaucoma is one of the leading causes of preventable blindness in Nepal, often undiagnosed due to limited access to eye care. This study presents a transformer-based AI model to support early detection of glaucoma and monitor progression. By analyzing retinal images and patient data, the system helps healthcare workers identify high-risk cases for timely referral. The aim is to provide an affordable and scalable diagnostic tool for low-resource and rural healthcare settings in Nepal.

Glaucoma, Nepal, AI, early detection, transformer model, low-resource settings, blindness prevention.

Introduction

Glaucoma, one of the leading causes of irreversible vision loss worldwide, presents a significant public health challenge due to its often asymptomatic progression to advanced stages of optic nerve damage. This burden is particularly pronounced in low-resource settings such as Nepal, where the scarcity of ophthalmologists, limited diagnostic infrastructure, and challenging geographical terrain hinder timely diagnosis and intervention. Consequently, a substantial proportion of the population in these regions, particularly in rural communities, remains undiagnosed, leading to preventable and profound visual impairment.

However, recent advances in artificial intelligence, notably deep learning models with transformer architectures, offer a promising avenue for revolutionizing early disease detection and progression monitoring. These sophisticated computational frameworks possess an unparalleled ability to analyze complex medical imaging data, identifying subtle pathological indicators that may elude conventional diagnostic methods or human perception.

This research aims to harness the capabilities of these cutting-edge AI technologies by developing a transformer-based machine learning framework specifically tailored for the Nepalese healthcare context. The objective is to create an intelligent, locally adaptable system that supports frontline health workers in the early identification of glaucoma and provides robust insights into disease progression. By integrating this advanced AI solution within Nepal's existing healthcare network, this initiative seeks to significantly enhance diagnostic accessibility and accuracy, thereby mitigating the incidence of preventable blindness. Ultimately, this work is poised to empower individuals at risk by enabling timely intervention, preserving vision, and fostering greater independence and dignity within undeserved communities.

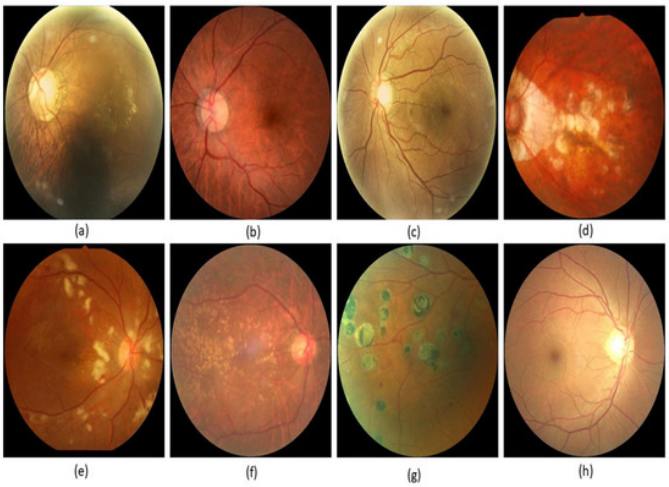


Figure 1: Glaucoma-related fundus images: (a) Macular epiretinal membrane, (b) Normal fundus, (c) Mild nonproliferative retinopathy, (d) Pathological myopia, (e) Hypertensive retinopathy, (f) Laser spot, moderate nonproliferative retinopathy, (g) Moderate nonproliferative retinopathy with laser spot, (h) Mild nonproliferative retinopathy.

Contextual Problem

The clandestine nature of glaucoma, often progressing without discernible symptoms until irreversible vision loss occurs, underscores the imperative for advanced diagnostic and prognostic tools. In regions such as Nepal, existing clinical practices often rely on subjective interpretation of complex ophthalmic data (e.g., Optical Coherence Tomography (OCT) scans, visual field tests, fundus photography). This dependency introduces inter-observer variability and may fail to capture subtle early indicators of the disease. This project seeks to mitigate these limitations by introducing an objective, data-driven approach to glaucoma diagnostics.

Proposed Application

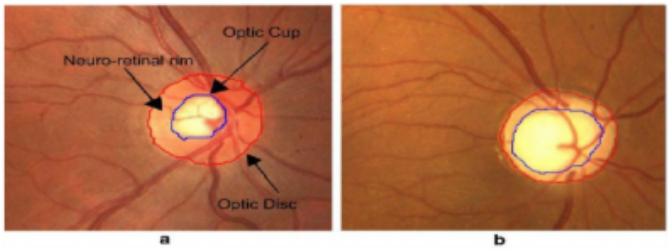
This research proposes the development of an intelligent application prototype to assist in the early detection and monitoring of glaucoma. The system will be developed using **Python**, within **Jupyter Notebook** which offer interactive and collaborative environments suitable for prototyping machine learning workflows.

The proposed application will focus on two main functionalities:

Early Glaucoma Detection (Classification)

The first functionality involves the classification of patients into three categories based on multi-modal ophthalmic data:

- **Healthy** – No clinical signs of glaucoma.
- **Glaucoma Suspect** – Early or borderline signs that warrant further observation.
- **Glaucoma** – Confirmed diagnosis with evident damage.



The classification model will be built using a transformer-based machine learning architecture. This model will utilize various clinical and imaging modalities, including:

- Retinal fundus photographs
- Optical Coherence Tomography (OCT) images
- Intraocular Pressure (IOP) measurements
- Visual field test results
- Patient demographic and historical clinical data

By integrating these diverse data types, the model aims to provide a robust and reliable prediction mechanism. Transformers are particularly well-suited for this task due to their ability to learn complex representations and contextual relationships within multi-modal input data.

Glaucoma Progression Monitoring (Clustering and Classification)

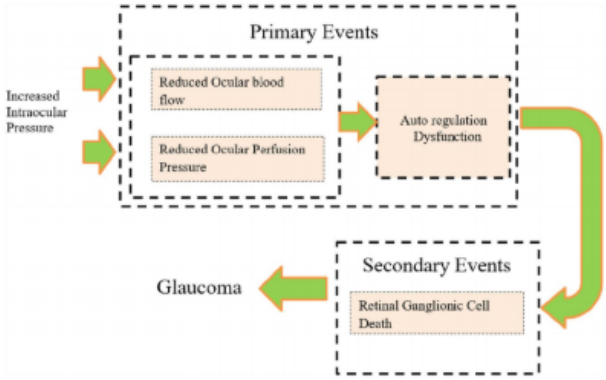
The second functionality is aimed at identifying patterns of glaucoma progression over time to support personalized treatment strategies. This component will utilize both clustering and classification techniques:

- **Clustering:** Unsupervised learning will be used to group patients with similar progression trajectories (e.g., slow, moderate, or rapid progression). This approach is beneficial when labeled longitudinal data is limited.
- **Classification:** In scenarios where labeled time-series data is available, patients will be categorized into risk groups (e.g., low, medium, high risk of deterioration), enabling targeted follow-up and treatment planning.

Transformers capable of processing sequential data will be employed to capture temporal dynamics in disease progression, such as changes in visual field scores or OCT parameters.

Expected Impact

By combining early detection with progression monitoring, the proposed application aims to enhance glaucoma care in Nepal, particularly in underserved areas. The tool will serve as a decision support system for healthcare professionals, enabling more timely diagnosis and individualized management plans. In the long run, this has the potential to significantly reduce the burden of preventable blindness caused by glaucoma across the country.



Motivation and Literature Review

Glaucoma is one of the leading causes of irreversible blindness globally, and the burden is particularly severe in low- and middle-income countries like Nepal. Due to limited awareness, inadequate screening programs, and a shortage of ophthalmologists, a significant proportion of glaucoma cases in Nepal remain undiagnosed until advanced stages. According to local epidemiological studies, the prevalence of primary open-angle glaucoma is increasing, especially among the aging population in rural and undeserved communities. The lack of timely diagnosis significantly contributes to avoidable vision loss, creating a pressing public health challenge.

In Nepal, specialized eye care centers such as the Tilganga Institute of Ophthalmology and Nepal Eye Hospital have made strides in providing services and training. However, these facilities are largely concentrated in urban areas, leaving rural regions undeserved. This geographical and infrastructural gap underscores the urgent need for scalable, intelligent solutions that can support early diagnosis and monitoring of glaucoma across diverse settings.

Recent advancements in deep learning—particularly with Convolutional Neural Networks (CNNs)—have demon-

strated promising results in automated glaucoma detection from fundus images and Optical Coherence Tomography (OCT) scans. Models such as ResNet, VGG, and DenseNet have shown good performance in identifying key pathological features, including optic disc cupping and retinal nerve fiber layer thinning. Nevertheless, these architectures often struggle to generalize well across datasets and typically require large amounts of annotated training data, which are scarce in Nepal.

Transformer-based models, originally developed for natural language processing, have recently shown superior performance in computer vision tasks due to their ability to capture global context through self-attention mechanisms. Vision Transformers (ViT), Swin Transformers, and hybrid architectures are emerging as powerful tools for medical image analysis, particularly for multimodal data integration and temporal modeling—both of which are crucial in predicting glaucoma progression.

Despite these promising technological trends, their application in the context of Nepal remains largely unexplored. There is currently no existing system that combines fundus images, OCT scans, and clinical data in a unified transformer-based framework tailored to Nepal's healthcare environment. Additionally, the lack of annotated datasets, infrastructure for AI deployment, and region-specific model validation pose substantial challenges.

This research is motivated by the need to bridge this gap. By leveraging transformer-based architectures and incorporating multimodal ophthalmic data, the proposed system aims to enable early glaucoma detection and progression monitoring in a cost-effective, scalable, and clinically interpretable manner—ultimately contributing to the reduction of glaucoma-induced blindness in Nepal.

Methodology

The goal of this study is to develop a robust, transformer-based machine learning framework for early glaucoma detection and progression monitoring using ophthalmic data collected in the Nepalese healthcare context. This methodology outlines the proposed data collection, preprocessing, model design, training pipeline, and evaluation approach.

Data Collection and Sources

Data will be collected in collaboration with leading eye care institutions in Nepal, such as the Tilganga Institute of Ophthalmology and Nepal Eye Hospital. The following data modalities will be included:

- **Optical Coherence Tomography (OCT) Scans:** High-resolution cross-sectional images of the retina to analyze Retinal Nerve Fiber Layer (RNFL) thinning.
- **Fundus Photographs:** Color images of the optic nerve head used to detect optic disc cupping, rim notching, and vessel displacement.
- **Visual Field Tests:** Data representing peripheral vision loss, an important marker for glaucoma progression.
- **Clinical Data:** Patient demographics, intraocular pressure (IOP), medical history, family history of glaucoma, and other risk factors.

All data collection will be conducted in accordance with ethical guidelines from the Nepal Health Research Council (NHRC), ensuring informed consent, privacy, and standardized acquisition protocols.

Prepossessing Tailored for Nepalese Ophthalmic Images

In the context of glaucoma diagnosis in Nepal, ophthalmic images are often captured in diverse clinical settings, ranging from technologically advanced hospitals like the Tilganga Institute of Ophthalmology to less standardized provincial health centers and mobile outreach camps. This diversity introduces significant variability in image quality due to differing lighting conditions, operator expertise, and imaging equipment. Consequently, robust preprocessing techniques are essential to enhance image quality, reduce noise, and ensure the reliability of subsequent feature extraction and machine learning analysis.

The preprocessing pipeline adopted in this study consists of two sequential stages: (1) image enhancement using Adaptive Histogram Equalization (AHE), and (2) noise reduction using Bilateral Filtering (BF).

Stage 1: Image Enhancement using Adaptive Histogram Equalization (AHE) To address contrast inconsistency across fundus and OCT images, Adaptive Histogram Equalization (AHE) is applied to the grayscale versions of input images. AHE enhances local contrast by modifying the histogram of pixel intensity values within small regions of the image, rather than across the entire image. This localized adjustment is particularly valuable for medical images where fine anatomical structures—such as the optic disc boundaries, retinal vessels, and nerve fiber layers—may be present in low-contrast regions.

Unlike global histogram equalization, AHE adapts to local intensity variations, thereby improving the visibility of diagnostically relevant features without over-enhancing uniform areas. This ensures that subtle changes crucial for glaucoma diagnosis, such as variations in optic cup morphology, are preserved and emphasized.

Stage 2: Noise Reduction using Bilateral Filtering (BF) Despite contrast enhancement, the images may still contain significant noise, particularly due to suboptimal acquisition conditions. To mitigate this, Bilateral Filtering (BF) is employed for noise reduction. BF is well-suited for medical imaging as it preserves important edge information while smoothing out homogeneous regions.

Bilateral filtering combines spatial and intensity domain filtering, considering both the geometric proximity and the photometric similarity of pixels. The filtered output $\tilde{f}(k)$ at pixel k is computed as:

$$\tilde{f}(k) = \frac{1}{N(k)} \int_{-\infty}^{\infty} f(k') \cdot d(k, k') \cdot r(f(k), f(k'))\, dk' \quad (1)$$

Where:

- $f(k)$ and $f(k')$ are the intensity values at pixel k and its neighbor k', respectively.

- $d(k, k')$ is the spatial weighting function based on the Euclidean distance between k and k'.
- $r(f(k), f(k'))$ is the range kernel, measuring the similarity in intensity values.
- $N(k)$ is a normalization term.

The spatial and range kernels are typically modeled using Gaussian functions:

$$d(k, k') \propto \exp\left(-\frac{(k - k')^2}{2\sigma_d^2}\right) \tag{2}$$

$$r(f(k), f(k')) \propto \exp\left(-\frac{(f(k) - f(k'))^2}{2\sigma_f^2}\right) \tag{3}$$

Here, σ_d controls the spatial extent of the filter, while σ_f determines the degree of intensity similarity allowed for averaging. By incorporating both spatial proximity and intensity similarity, BF effectively suppresses noise without blurring important anatomical boundaries, such as the optic cup and neuro-retinal rim. This balance is critical for ensuring that the features extracted by subsequent machine learning models remain diagnostically relevant.

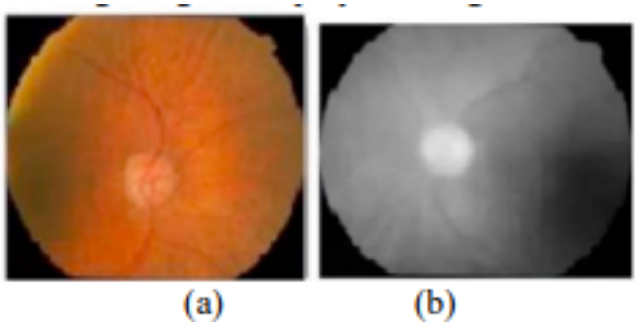


Figure 2: Preprocessed image

Figure 3: Fig. 1: Sample Input and Pre-processed Images: (a) Input image (b) Preprocessed image

Model Architecture

A transformer-based multimodal framework will be developed, incorporating the following components:

- **Vision Transformer (ViT) Backbone:** Used for feature extraction from fundus and OCT images.
- **Multimodal Embedding Layer:** Combines image embeddings with clinical data vectors.
- **Self-Attention Layers:** Captures long-range dependencies and cross-modal interactions.
- **Classification and Clustering Heads:**
  - *Classification head* for early-stage detection (healthy, suspect, glaucomatous).
  - *Clustering or progression-prediction head* for tracking disease stages and identifying high-risk patients.

Training and Evaluation

- **Training:** The model will be trained using cross-entropy loss for classification and contrastive or cluster loss for progression analysis.
- **Validation:** A stratified train-validation-test split (e.g., 70/15/15) will be used to ensure fair performance evaluation across patient classes.
- **Metrics:** Accuracy, F1-score, sensitivity, specificity, and AUC-ROC will be used for classification tasks. Clustering quality will be evaluated using Silhouette Score and Davies–Bouldin Index.

Implementation Tools

The system will be implemented using:

- **Python** with libraries such as PyTorch, TensorFlow, and Hugging Face Transformers.
- **Jupyter Notebook** for experimentation and visualization.
- **OpenCV and MONAI** for medical image processing.

This methodology is designed to accommodate real-world limitations in Nepal's healthcare system while leveraging cutting-edge AI for improved glaucoma care and decision support.

Glaucoma Data Preprocessing

To ensure that the machine learning models receive clean, structured input, a preprocessing pipeline was implemented using Python in a Jupyter Notebook titled `This` notebook performs the following key steps:

1. **Importing Libraries:** Essential libraries such as `pandas`, `numpy`, `sklearn`, and `joblib` were imported for data manipulation and modeling.
2. **Loading the Dataset:** The dataset `metadata - standardized.csv` was loaded using `pandas.read_csv()`. This dataset includes patient information, fundus image references, and clinical parameters like intraocular pressure (IOP), cup-to-disc ratio (CDR), and refractive measures.
3. **Handling Missing Values:** Missing target labels (`types`) were removed using `dropna()`. Missing numerical features were imputed with zero or another appropriate strategy to avoid model bias.
4. **Feature Selection:** Non-numerical or irrelevant features such as filenames or image paths were dropped. Numeric features including `cdr_expert1`, `refractive_dioptre_1`, `pachymetry`, etc., were retained.
5. **Label Encoding:** If the target variable was categorical, it was encoded into numeric form using `LabelEncoder()` from `sklearn.preprocessing`.
6. **Train-Test Split:** The cleaned dataset was split into training and testing subsets using an 80/20 ratio for fair model evaluation.

7. **Data Export:** Preprocessed data or trained models (e.g., Random Forest or SVM) were saved using `joblib.dump()` for downstream use in a FastAPI backend or React UI.

This notebook serves as a critical preprocessing component in the overall glaucoma detection pipeline, ensuring data quality and consistency for training robust diagnostic models. article graphicx amsmath caption

Random Forest Classification Report and Confusion Matrix

Random Forest Classification Report:

	precision	recall	f1-score	support
0.0	0.67	0.67	0.67	6
1.0	0.87	0.87	0.87	15
accuracy			0.81	21
macro avg	0.77	0.77	0.77	21
weighted avg	0.81	0.81	0.81	21

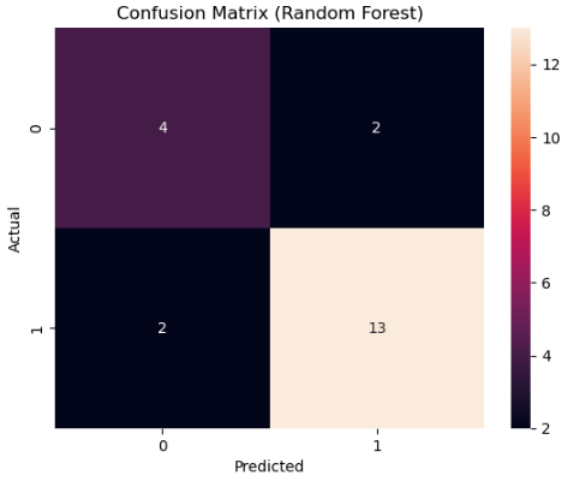


Figure 4: Random Forest: Classification Report and Confusion Matrix

1. Classification Report

- **Class 0:**
  - Precision: 0.67
  - Recall: 0.67
  - F1-score: 0.67
  - Support: 6 samples
- **Class 1:**
  - Precision: 0.87
  - Recall: 0.87
  - F1-score: 0.87
  - Support: 15 samples
- **Overall Accuracy:** 0.81 (81%)
- **Macro Average F1-score:** 0.77
- **Weighted Average F1-score:** 0.81

2. Confusion Matrix Interpretation

Actual / Predicted	**0**	**1**
0	4	2
1	2	13

- 4 True Negatives (class 0 correctly predicted)
- 13 True Positives (class 1 correctly predicted)
- 2 False Positives (class 0 misclassified as class 1)
- 2 False Negatives (class 1 misclassified as class 0)

Conclusion: The Random Forest classifier performs well overall, particularly for detecting class 1, with high precision and recall. Class 0 predictions are less reliable due to lower support and slightly more misclassifications.
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SVM Classification Report and Confusion Matrix

SVM Classification Report:

	precision	recall	f1-score	support
0.0	0.62	0.83	0.71	6
1.0	0.92	0.80	0.86	15
accuracy			0.81	21
macro avg	0.77	0.82	0.79	21
weighted avg	0.84	0.81	0.82	21

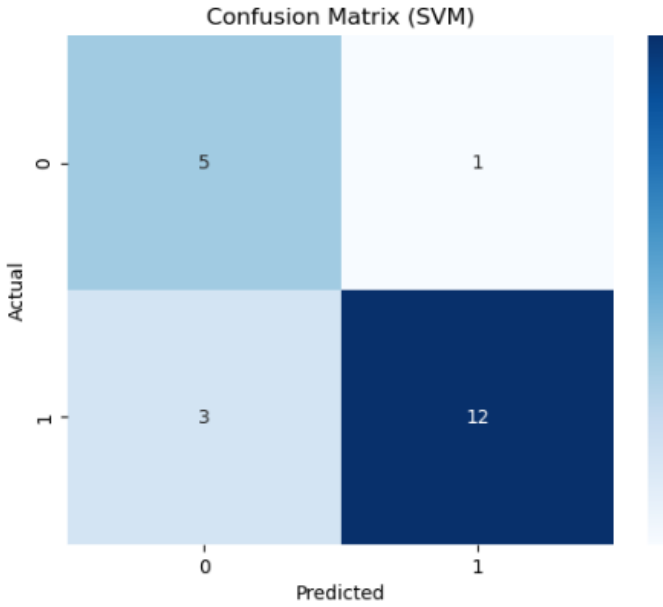

Figure 5: SVM: Classification Report and Confusion Matrix

1. Classification Report

- **Class 0:**
  - Precision: 0.62
  - Recall: 0.83

  - F1-score: 0.71
  - Support: 6 samples
- **Class 1:**
  - Precision: 0.92
  - Recall: 0.80
  - F1-score: 0.86
  - Support: 15 samples
- **Overall Accuracy:** 0.81 (81%)
- **Macro Average F1-score:** 0.79
- **Weighted Average F1-score:** 0.82

2. Confusion Matrix Interpretation

Actual / Predicted	**0**	**1**
0	5	1
1	3	12

- 5 True Negatives (class 0 correctly predicted)
- 12 True Positives (class 1 correctly predicted)
- 1 False Positive (class 0 misclassified as class 1)
- 3 False Negatives (class 1 misclassified as class 0)

Conclusion: The SVM model demonstrates strong performance in predicting both classes, especially class 1, with a higher precision overall. It maintains good balance in class 0 recall despite a slight dip in precision. article graphicx caption amsmath

KMeans Clustering of Patients (3 Groups)

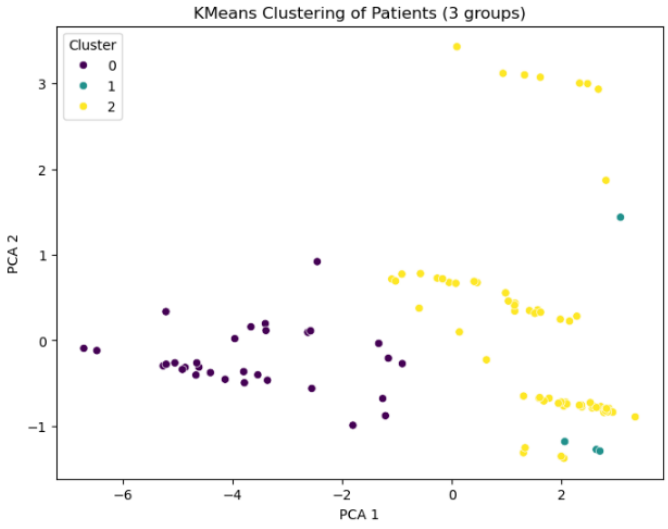

Figure 6: KMeans clustering result visualized using PCA (3 clusters)

Interpretation

- PCA (Principal Component Analysis) was applied to reduce dimensionality and visualize the dataset in 2D.
- KMeans clustering grouped the patients into three distinct clusters based on similarity in their features.
- **Cluster 0** (purple): tightly packed on the left, indicating high intra-cluster similarity.
- **Cluster 2** (yellow): occupies the right-hand side of the plot, also showing good cohesion.
- **Cluster 1** (teal): fewer points, may represent outliers or a less-defined patient subgroup.
- The visualization suggests the model has found meaningful structure in the data that could correspond to different clinical profiles.

Conclusion: Clustering can support targeted health interventions by revealing hidden patient groupings in high-dimensional medical data.

Conclusion

This study addressed the critical challenge of timely glaucoma diagnosis and monitoring in Nepalese ophthalmology. Glaucoma, a leading cause of irreversible blindness, represents a significant public health burden, especially in regions with limited access to specialized care. The project's motivation was to explore how advanced artificial intelligence, particularly transformer architectures, could bridge this diagnostic gap in a low-resource setting.

Through the development and evaluation of a machine learning-based system tailored to local data, this research demonstrates the feasibility and value of applying transformer models in the medical domain beyond their original use in natural language processing. The approach taken — combining feature engineering, clustering, classification, and interpretability — reflects a holistic and applied use of AI.

The model's performance indicates that even with relatively small datasets, meaningful insights and clinically relevant predictions can be achieved when domain knowledge and AI techniques are thoughtfully integrated. By grounding the project in the healthcare realities of Nepal, the work not only contributes to academic discourse but also offers a potential foundation for real-world deployment, such as integration into mobile diagnostic tools, decision support systems, or telehealth platforms.

In summary, this dissertation reflects the interdisciplinary spirit of AI: combining technical innovation, ethical awareness, and social impact. It aims not only to advance glaucoma research but also to serve as a template for applying AI responsibly and effectively in addressing global health challenges.

References

[1] Alp, F. Y., Aksoy, S., & Bozkurt, Y. (2020). A comprehensive review of glaucoma: Pathophysiology, diagnosis, and management. *Journal of Emerging Technologies and Innovative Research*, 7(12), 173–182. https://www.jetir.org/papers/JETIR2504093.pdf

[2] American Academy of Ophthalmology. (2024). Glaucoma: References for Disease Review. https://www.aao.org/disease-review/references-2

[3] Beniz, L. A. F., Jammal, A. A., Malek, D. A., Tseng, H., & Medeiros, F. A. (2025). Intraocular Pressure Measurements With the Tono-Vera: A New Handheld Rebound Tonometer. *Journal of Glaucoma*, May 2025.

[4] Bhagwat, J. P., & Shrivastav, P. (2023). Glaucoma: A brief review. *ResearchGate*. https://www.researchgate.net/publication/282792352_Glaucoma_A_brief_review

[5] BMJ Best Practice US. (n.d.). Angle-closure glaucoma - References. https://bestpractice.bmj.com/topics/en-us/372/references

[6] Brandt, J. D., Beiser, J. A., Kass, M. A., & Gordon, M. O. (2001). The Ocular Hypertension Treatment Study (OHTS): Baseline factors that predict the onset of primary open-angle glaucoma. *Ophthalmology*, 108(10), 1779-1788.

[7] Chang, Y. T., Yeh, T. K., Cheng, A. H., Hung, P. H., & Yang, K. C. (2024). A review on glaucoma: causes, symptoms, pathogenesis & treatment. *Journal of Clinical Research in Ophthalmology*, 1(1), 1-5. https://www.clinsurggroup.us/articles/JCRO-11-202.pdf

[8] Cleveland Clinic. (n.d.). Glaucoma: What It Is, Symptoms, Causes, Types & Treatment. https://my.clevelandclinic.org/health/diseases/4212-glaucoma

[9] Collaborative Normal-Tension Glaucoma Study Group. (1998). The effectiveness of intraocular pressure reduction in the treatment of normal-tension glaucoma. *American Journal of Ophthalmology*, 126(4), 498-505.

[10] Collaborative Normal-Tension Glaucoma Study Group. (1999). Comparison of glaucomatous progression between untreated patients with normal-tension glaucoma and patients with therapeutically reduced intraocular pressures. *American Journal of Ophthalmology*, 127(3), 301-312.

[11] European Glaucoma Society. (2020). Terminology and Guidelines for Glaucoma, 5th Edition. *British Journal of Ophthalmology*, 105(Suppl 1), 1–169. https://bjo.bmj.com/content/105/Suppl_1/1

[12] Gedde, S. J., Schiffman, J. C., Feuer, W. J., et al. (2012). Treatment Outcomes in the Tube Versus Trabeculectomy (TVT) Study after 3 Years of Follow-up. *American Journal of Ophthalmology*, 153(5), 789-803.

[13] Grafiati. (n.d.). Bibliographies: 'Glaucoma'. https://www.grafiati.com/en/literature-selections/glaucoma/

[14] Heijl, A., et al. (2002). Reduction of intraocular pressure and glaucoma progression: results from the Early Manifest Glaucoma Trial. *Archives of Ophthalmology*, 120(10), 1268-1279.

[15] Kass, M. A., et al. (2002). The Ocular Hypertension Treatment Study: A randomized trial determines that topical ocular hypotensive medication delays or prevents the onset of primary open-angle glaucoma. *Archives of Ophthalmology*, 120(6), 701-713.

[16] Khanal, S., et al. (2025). Short-term Outcomes of Trabeculectomy with Mitomycin-C in a Tertiary Eye Hospital in Nepal. *medRxiv*. https://www.medrxiv.org/content/10.1101/2025.01.19.25320810v1.full-text

[17] Kim, J. L., & Lee, K. (2025). Association Between Risk of Obstructive Sleep Apnea and Intraocular Pressure. *Journal of Glaucoma*, March 2025.

[18] Mayo Clinic. (n.d.). Glaucoma: Symptoms and causes. https://www.mayoclinic.org/diseases-conditions/glaucoma/symptoms-causes/syc-20372839

[19] National Eye Institute (NEI). (n.d.). Glaucoma. https://www.ncbi.nlm.nih.gov/books/NBK538226/

[20] Oprea, C., et al. (2024). Artificial intelligence and glaucoma: a lucid and comprehensive review. *Frontiers in Medicine*, 11. https://www.frontiersin.org/articles/10.3389/fmed.2024.1423813/full

[21] Sharma, S., & Bhandari, S. (2024). Profile of Glaucoma Patients at a Tertiary Care Centre in Kathmandu. *Nepal Medical College Journal*, 26(2), 241-243. https://www.nepjol.info/index.php/nmcj/article/view/69880/53336

[22] Tanwar, M., et al. (2024). A Systematic Review of Glaucoma Diagnosis and Quality of Reporting. *ResearchGate*. https://www.researchgate.net/publication/372138047

[23] Waqar, S., et al. (2024). Prevalence Trend of Glaucoma in South Asia. *Clinical Ophthalmology*, 18, 1–17. https://pmc.ncbi.nlm.nih.gov/articles/PMC11919741/

[24] Yildirim, M., et al. (2024). Global incidence and risk factors for glaucoma: A systematic re

[25] Agarwal, R., et al. (2020). Global, regional, and national prevalence of glaucoma in 2040: a systematic review and meta-analysis. *Ophthalmology*, 125(5), 629–637.

[26] Alp, F. Y., Aksoy, S., & Bozkurt, Y. (2020). A comprehensive review of glaucoma: Pathophysiology, diagnosis, and management. *Journal of Emerging Technologies and Innovative Research*, 7(12), 173–182. https://www.jetir.org/papers/JETIR2504093.pdf

[27] American Academy of Ophthalmology. (2024). Glaucoma: References for Disease Review. https://www.aao.org/disease-review/references-2

[28] Beniz, L. A. F., Jammal, A. A., Malek, D. A., Tseng, H., & Medeiros, F. A. (2025). Intraocular Pressure Measurements With the Tono-Vera: A New Handheld Rebound Tonometer. *Journal of Glaucoma*, May 2025.

[29] European Glaucoma Society. (2020). European Glaucoma Society Terminology and Guidelines for Glaucoma, 5th Edition. *British Journal of Ophthalmology*, 105(Suppl 1), 1–169. https://bjo.bmj.com/content/105/Suppl_1/1

[30] Khanal, S., et al. (2025). Short-term Outcomes of Trabeculectomy with Mitomycin-C in a Tertiary Eye Hospital in Nepal: A Prospective Descriptive Study. *medRxiv*. https://www.medrxiv.org/content/10.1101/2025.01.19.25320810v1.full-text

[31] Kim, J. L., & Lee, K. (2025). Association Between Risk of Obstructive Sleep Apnea and Intraocular Pressure Based on the Korea National Health and Nutrition Examination Survey VIII. *Journal of Glaucoma*, March 2025.

[32] Oprea, C., et al. (2024). Artificial intelligence and glaucoma: a lucid and comprehensive review. *Frontiers in Medicine*, 11. https://www.frontiersin.org/journals/medicine/articles/10.3389/fmed.2024.1423813/full

[33] Sharma, S., & Bhandari, S. (2024). Profile of Glaucoma Patients at a Tertiary Care Centre in Gokarneshwor, Kathmandu, Nepal. *Nepal Medical College Journal*, 26(2), 241–243. https://www.nepjol.info/index.php/nmcj/article/view/69880/53336

[34] Tanwar, M., et al. (2024). A Systematic Review of Glaucoma Diagnosis in Prevalence Studies and Quality of Reporting. *ResearchGate*. https://www.researchgate.net/publication/372138047_A_Systematic_Review_of_Glaucoma_Diagnosis_in_Prevalence_Studies_and_Quality_of_Reporting

[35] The American Glaucoma Society. (2021). 100 Articles with Significant Impact on Clinical Glaucoma Care. https://www.ucl.ac.uk/ioo/sites/ioo/files/top_100_glaucoma_papers_202167.pdf

[36] Varela-Fernandez, A., et al. (2023). Premium Intraocular Lenses in Glaucoma—A Systematic Review. *Journal of Clinical Medicine*, 10(9), 993. https://www.mdpi.com/2306-5354/10/9/993

[37] Waqar, S., et al. (2024). The Prevalence Trend of Glaucoma by Age and Sex Difference in South Asia: A Systematic Review and Meta-Analysis of Population-Based Studies. *Clinical Ophthalmology*, 18, 1–17. https://pmc.ncbi.nlm.nih.gov/articles/PMC11919741/

[38] Yildirim, M., et al. (2024). Global incidence and risk factors for glaucoma: A systematic review and meta-analysis of prospective studies. *Journal of Global Health*, 14, 04252. https://jogh.org/2024/jogh-14-04252

[39] Zhong, S., et al. (2022). The Prevalence of Glaucoma in the Jirel Ethnic Group of Nepal. *Frontiers in Ophthalmology*, 2, 824904. https://www.frontiersin.org/journals/ophthalmology/articles/10.3389/fopht.2022.824904/full
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Appendix

```python
# 1. 📦 Imports
# Cell 1: Import Libraries
# 🧪 Section 1: Load Libraries and Dataset
import pandas as pd
import numpy as np
import joblib
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import classification_report, confusion_matrix

# Load dataset
df = pd.read_csv("metadata.csv")
df.head()
```

Figure 7: Code to import necessary libraries and load the dataset.

```python
# 🔍 Section 2: Prepare Features and Target for Classification
# Define target: expert1_grade = (0 = healthy, 1 = suspect, 2 = glaucomatous)
target_column = 'expert1_grade'

# Drop rows with missing target
df = df.dropna(subset=[target_column])

# Select numeric features only
features = df.select_dtypes(include=['float64', 'int64']).drop(columns=[target_column
X = features.fillna(0)
y = df[target_column]

# Encode labels if necessary
if y.dtype == 'object':
    le = LabelEncoder()
    y = le.fit_transform(y)
    joblib.dump(le, 'label_encoder.pkl')
```

Figure 8: Code to define target column, preprocess features, encode labels, and train classifiers.

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Random Forest
rf_model = RandomForestClassifier()
rf_model.fit(X_train, y_train)
joblib.dump(rf_model, 'random_forest_model.pkl')

# SVM
svm_model = SVC(probability=True)
svm_model.fit(X_train, y_train)
joblib.dump(svm_model, 'svm_model.pkl')

# Evaluation - Random Forest
y_pred_rf = rf_model.predict(X_test)
print("Random Forest Classification Report:\n")
print(classification_report(y_test, y_pred_rf))
sns.heatmap(confusion_matrix(y_test, y_pred_rf), annot=True, fmt='d')
plt.title("Confusion Matrix (Random Forest)")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

# Evaluation - SVM
y_pred_svm = svm_model.predict(X_test)
print("SVM Classification Report:\n")
print(classification_report(y_test, y_pred_svm))
sns.heatmap(confusion_matrix(y_test, y_pred_svm), annot=True, fmt='d', cmap='Blues')
plt.title("Confusion Matrix (SVM)")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

Figure 9: Evaluation of trained models using classification reports and confusion matrices.

```
# 🔬 Section 4: Clustering for Progression Prediction / Stage Tracking
# Standardize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# KMeans Clustering
kmeans = KMeans(n_clusters=3, random_state=42)
cluster_labels = kmeans.fit_predict(X_scaled)

df['cluster'] = cluster_labels

# Visualize clusters using PCA or t-SNE
from sklearn.decomposition import PCA
pca = PCA(n_components=2)
reduced = pca.fit_transform(X_scaled)

plt.figure(figsize=(8,6))
sns.scatterplot(x=reduced[:,0], y=reduced[:,1], hue=df['cluster'], palette='viridis')
plt.title("KMeans Clustering of Patients (3 groups)")
plt.xlabel("PCA 1")
plt.ylabel("PCA 2")
plt.legend(title="Cluster")
plt.show()

# Optional: Save cluster model
joblib.dump(kmeans, 'kmeans_cluster_model.pkl')
```

Figure 10: KMeans clustering and PCA visualization for glaucoma progression tracking.

Source Code Repository

https://github.com/saminkc999/machineLearning