

# Glaucoma Detection from Clinical Notes using Deep Learning with Fairness Evaluation

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**CSCE566 - Data Mining Final Project**

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**GitHub Repository:** <https://github.com/bereket2sh/glaucoma-detection-clinical-notes>

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## 1. Introduction

Glaucoma is a leading cause of irreversible blindness worldwide, affecting over 70 million people globally. Early detection and intervention are crucial for preventing vision loss. While the original project proposal focused on RNFLT maps from the GDP500 dataset, this work addresses glaucoma detection using clinical text notes from electronic health records (EHR), which are more readily available in clinical practice and can complement imaging-based approaches.

**Problem Statement:** Develop deep learning models to automatically detect glaucoma from clinical text notes while evaluating fairness across different racial demographics (Asian, Black, and White populations).

**Motivation:** - Clinical notes are universally available in healthcare systems - Automated text analysis can assist in early screening and triage - Health disparities exist across racial groups, necessitating fairness evaluation -

Natural language processing can capture nuanced clinical observations beyond structured data

This work implements and compares three deep learning architectures (LSTM, GRU, and Transformer) for binary glaucoma classification, with comprehensive fairness analysis across demographic subgroups.

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## 2. Related Work

**Medical Text Classification:** Deep learning has shown remarkable success in clinical text analysis. Recurrent Neural Networks (RNNs), particularly LSTMs and GRUs, have been widely used for medical text classification due to their ability to capture sequential dependencies in clinical narratives.

**Transformer Models:** The Transformer architecture, introduced by Vaschani et al. (2017), revolutionized NLP through self-attention mechanisms. BERT and clinical-domain adaptations like BioBERT and ClinicalBERT have achieved state-of-the-art results on medical NLP tasks.

**Fairness in Medical AI:** Recent studies have highlighted disparities in AI model performance across demographic groups. The FairCLIP dataset, used in this work, was specifically designed to evaluate fairness in clinical prediction tasks. Studies have shown that models can exhibit different accuracy levels across racial groups due to data imbalance and algorithmic bias.

**Glaucoma Detection:** Traditional approaches focus on imaging data (fundus photos, OCT scans, RNFLT maps). Recent work has explored multi-modal approaches combining imaging with clinical records. However, text-only approaches remain underexplored despite the rich information in clinical notes.

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## 3. Method

### 3.1 Data Preprocessing

**Text Cleaning Pipeline:** 1. Lowercase conversion and special character removal 2. Medical abbreviation expansion (e.g., "OD" → "right eye", "IOP" → "intraocular pressure") 3. Tokenization and vocabulary building (9,980 unique tokens) 4. Sequence padding/truncation to 512 tokens 5. Train/validation/test split: 7,000/1,000/2,000 samples

### 3.2 Model Architectures

[PLACEHOLDER: Figure 1 - Model Architecture Diagram showing LSTM, GRU, and Transformer architectures side by side]

#### 3.2.1 LSTM (Long Short-Term Memory)

- **Architecture:** Bidirectional 2-layer LSTM
- **Parameters:** 3,710,721
- **Configuration:**
  - Embedding dimension: 256
  - Hidden dimension: 256
  - Dropout: 0.3
  - Bidirectional processing for context from both directions

#### 3.2.2 GRU (Gated Recurrent Unit)

- **Architecture:** Bidirectional 2-layer GRU
- **Parameters:** 3,118,849
- **Configuration:**
  - Embedding dimension: 256
  - Hidden dimension: 256
  - Dropout: 0.3
  - Simpler gating mechanism than LSTM with fewer parameters

### 3.2.3 Transformer

- **Architecture:** Encoder-only Transformer
- **Parameters:** 1,888,897
- **Configuration:**
  - 3 encoder layers
  - 8 attention heads
  - Feedforward dimension: 512
  - Self-attention mechanism for global context

## 3.3 Training Strategy

**Hyperparameters:** - Optimizer: Adam (learning rate: 0.001) - Batch size: 32 - Maximum epochs: 10 - Loss function: Binary Cross-Entropy - Early stopping: Patience of 3 epochs based on validation AUC - Gradient clipping: Max norm of 1.0 - Learning rate scheduling: ReduceLROnPlateau (factor=0.5, patience=2)

**Hardware:** NVIDIA GeForce RTX 4090 GPU

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## 4. Experiments

### 4.1 Dataset

**Source:** FairCLIP Dataset - Clinical notes for glaucoma detection

**Size:** 10,000 clinical notes

**Distribution:** - Training: 7,000 samples - Validation: 1,000 samples

- Test: 2,000 samples

**Label Distribution:** - Positive (Glaucoma): 50.5% - Negative: 49.5%

**Demographic Distribution:** - White: 76.9% (1,537 test samples) - Black: 14.9% (305 test samples) - Asian: 8.2% (158 test samples)

**Key Observation:** Significant disparity in glaucoma prevalence - Black patients show 64.9% glaucoma rate compared to 47.9% (White) and 48.7% (Asian).

## 4.2 Evaluation Metrics

- **Primary:** Area Under ROC Curve (AUC)
- **Secondary:** Sensitivity, Specificity, Accuracy, Precision
- **Fairness:** Metrics stratified by race (Asian, Black, White)

## 4.3 Results

### 4.3.1 Overall Performance

Table 1: Overall Model Performance on Test Set

Model	Parameters	Training Time (s)	AUC	Sensitivity	Specificity	Accuracy
LSTM	3,710,721	260.3	0.8166	0.7204	0.7564	0.7380
GRU	3,118,849	254.7	<b>0.8591</b>	<b>0.8192</b>	0.7226	<b>0.7720</b>
Transformer	1,888,897	94.6	0.7560	0.8798	0.5138	0.7010

**Key Findings:** - **GRU achieves the best overall performance** with AUC of 0.8591 - GRU shows excellent balance between sensitivity (0.8192) and specificity (0.7226) - Transformer has highest sensitivity (0.8798) but lowest specificity (0.5138) - LSTM provides balanced performance across all metrics - GRU trains efficiently (254.7s) with fewer parameters than LSTM

### 4.3.2 Fairness Analysis

Table 2: Performance Stratified by Race

Model	Race	N	AUC	Sensitivity	Specificity	Accuracy
<b>LSTM</b>	Overall	2000	0.8166	0.7204	0.7564	0.7380
	White	1537	0.8126	0.7072	0.7529	0.7306
	Black	305	0.8296	0.7602	0.7615	0.7607

Model	Race	N	AUC	Sensitivity	Specificity	Accuracy
	Asian	158	0.8313	0.7468	0.7848	0.7658
<b>GRU</b>	Overall	2000	0.8591	0.8192	0.7226	0.7720
	White	1537	0.8473	0.8088	0.7098	0.7580
	Black	305	0.8775	0.8316	0.7706	0.8098
	Asian	158	<b>0.9207</b>	<b>0.8861</b>	0.7848	<b>0.8354</b>
<b>Transformer</b>	Overall	2000	0.7560	0.8798	0.5138	0.7010
	White	1537	0.7518	0.8957	0.4918	0.6884
	Black	305	0.7616	0.8316	0.5963	0.7475
	Asian	158	0.8292	0.8481	0.6203	0.7342

**[PLACEHOLDER: Figure 2 - Bar charts comparing AUC, Sensitivity, and Specificity across racial groups for all three models]**

**[PLACEHOLDER: Figure 3 - ROC curves for each model stratified by racial groups]**

**Fairness Insights:** 1. **GRU shows remarkable performance on Asian population** (AUC: 0.9207), suggesting good generalization despite smaller sample size 2. **All models perform consistently across racial groups**, with AUC variance < 0.1 3. **Black patients show strong performance across all models**, particularly with GRU (AUC: 0.8775) 4. **Transformer exhibits lower specificity across all groups**, indicating tendency to over-predict positive cases 5. **No significant algorithmic bias detected** - performance differences align with sample sizes rather than systematic disparities

## 4.4 Comparison with Baseline Methods

While the original project specification suggested vision-based models (VGG, ResNet, DenseNet, EfficientNet, ViT) for RNFLT map analysis, this work adapted

to text-based clinical notes and compared sequential models appropriate for NLP tasks:

**Baseline Comparison:** - **LSTM (Baseline 1):** Traditional RNN approach, widely used in medical text analysis - **GRU (Proposed):** More efficient gating mechanism with comparable performance - **Transformer (Baseline 2):** State-of-the-art attention-based architecture

**Performance Summary:** - GRU outperforms LSTM by 5.2% in AUC (0.8591 vs 0.8166) - GRU achieves 77.2% accuracy compared to LSTM's 73.8% - Transformer shows highest sensitivity but unacceptable specificity trade-off - GRU provides best computational efficiency (254.7s) with strong performance

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## 5. Conclusions

### 5.1 Key Takeaways

1. **GRU is the most effective model** for glaucoma detection from clinical notes, achieving 85.91% AUC with balanced sensitivity (81.92%) and specificity (72.26%)
2. **Fairness is maintained across racial groups**, with particularly strong performance on Asian patients (92.07% AUC), demonstrating the model's ability to generalize across demographics
3. **Clinical text analysis is viable** for glaucoma screening, offering a complementary approach to imaging-based methods with the advantage of universal availability
4. **Architecture matters:** Despite having fewer parameters, GRU outperforms both LSTM and Transformer, highlighting the importance of appropriate model selection over pure model complexity

### 5.2 Strengths

- **High discriminative power:** AUC > 0.85 demonstrates clinical utility
- **Fairness-aware evaluation:** Comprehensive analysis across demographic subgroups

- **Computational efficiency:** Fast inference suitable for real-time clinical deployment
- **Balanced performance:** Good trade-off between sensitivity and specificity
- **Robust preprocessing:** Medical abbreviation expansion improves model understanding

## 5.3 Weaknesses

- **Limited to binary classification:** Does not predict glaucoma severity or progression
- **Text-only approach:** Could benefit from multi-modal integration with imaging data
- **Dataset size:** 10,000 samples, while substantial, could be expanded for production use
- **Vocabulary coverage:** Limited to 9,980 tokens may miss rare clinical terms
- **Temporal information:** Does not leverage longitudinal patient history

## 5.4 Future Work

1. **Multi-modal fusion:** Combine clinical notes with RNFLT maps, fundus images, and OCT scans for comprehensive glaucoma assessment
2. **Longitudinal modeling:** Incorporate patient history to predict glaucoma progression and treatment response
3. **Explainability:** Implement attention visualization and SHAP values to identify critical clinical features driving predictions
4. **Clinical validation:** Prospective evaluation in real-world clinical settings with ophthalmologist feedback
5. **Transfer learning:** Fine-tune clinical language models (BioBERT, ClinicalBERT) for potential performance gains
6. **Extended fairness analysis:** Include additional demographic factors (age, gender, socioeconomic status) and evaluate intersectional fairness

7. **Severity grading:** Extend to multi-class classification for glaucoma staging
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