



Intelligent System for Diabetes Prediction Using Deep Learning Techniques: An Applied Study on Saudi Patient Data

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Abstract

Early detection of diabetes remains a critical challenge in modern healthcare, directly influencing treatment outcomes and long-term patient well-being. This thesis aims to improve diagnostic accuracy through the development of an AI-based medical classification system using deep learning models applied to clinical laboratory images. The dataset, collected from medical image repositories, includes diverse visual samples such as glucose test strips, microscopic blood images, and metabolic biomarkers essential for diabetes diagnosis. The research begins with an extensive literature review comprising twelve scholarly papers: six that guided the initial model design and six integrated later to support and refine the theoretical framework.

Preprocessing steps—including image normalization, noise reduction, resizing, and contrast enhancement—were applied to prepare the data. Feature extraction and selection were performed using deep convolutional architectures. A Convolutional Neural Network (CNN), optimized using transfer learning and fine-tuned hyperparameters, was employed to build the classification model. The model achieved high predictive performance, reaching an accuracy of up to 98.4% on the processed dataset.

The study highlights the significant impact of image-based biomarkers, contrast patterns, and pixel-level abnormalities in improving early diabetes detection. Visual analyses—including activation maps, confusion matrices, and training-validation curves—further supported the interpretability of the results. The findings demonstrate the effectiveness of AI in accelerating medical diagnosis and enabling data-driven decision-making in clinical environments. This research lays a foundation for future real-time diagnostic tools using cloud infrastructure and live medical imaging streams.

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List of Abbreviations

- ANN: Artificial Neural Network
- API: Application Programming Interface
- AI: Artificial Intelligence
- AUC: Area Under the Curve
- BiLSTM: Bidirectional Long Short-Term Memory
- CNN: Convolutional Neural Network
- DeepONet: Deep Operator Network
- DT: Decision Tree
- GBM: Gradient Boosting Machine

- GridSearchCV: Grid Search with Cross-Validation
- GWO: Grey Wolf Optimizer
- IQR: Interquartile Range
- LDA: Latent Dirichlet Allocation
- LSTM: Long Short-Term Memory
- MAE: Mean Absolute Error
- MAPE: Mean Absolute Percentage Error
- MLMFN: Multi-Layered Memory Fusion Network
- ML: Machine Learning
- MLP: Multi-Layer Perceptron
- PR: Precision-Recall
- PSO: Particle Swarm Optimization
- RF: Random Forest
- R²: Coefficient of Determination
- RFE: Recursive Feature Elimination
- RMSE: Root Mean Square Error
- SGD: Stochastic Gradient Descent
- SGDAN: Spatio-Temporal Graph Dual Attention Network
- SHAP: SHapley Additive exPlanations
- SVM: Support Vector Machine
- XAI: Explainable Artificial Intelligence
- XGBoost: Extreme Gradient Boosting

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Chapter 1

Introduction

1.1 Problem Definition

Early detection of diabetes poses a significant challenge in modern healthcare, as delayed diagnosis often leads to severe complications such as cardiovascular disease, neuropathy, vision impairment, and long-term organ damage. Traditional diagnostic methods rely heavily on manual interpretation of laboratory results and medical images, which can be time-consuming, prone to human error, and dependent on the expertise of medical professionals. These limitations create delays in clinical decision-making and increase the risk of undetected early-stage diabetes.

Conventional machine-learning approaches often assume simplified patterns and struggle to capture the complex visual and biochemical variations present in medical images. They lack the ability to automatically extract deep hierarchical features that indicate early metabolic abnormalities. As a result, current diagnostic systems may fail to provide accurate or consistent predictions in real clinical environments. Therefore, there is a clear need for an intelligent, automated diagnostic framework capable of analyzing medical images, learning from subtle pixel-level patterns, and identifying early indicators of diabetes with higher accuracy and reliability.

1.2 Thesis Objectives

This thesis aims to design and evaluate an AI-based diagnostic framework for early detection of diabetes using medical laboratory images. The specific objectives are:

- 1.To explore and analyze real-world medical imaging data related to diabetes, and identify the most significant visual and biochemical indicators associated with early-stage diagnosis.
- 2.To build a robust preprocessing pipeline capable of handling image noise, variations in lighting, image resolution differences, and contrast enhancement to prepare images for deep learning.

3.To develop a deep learning model, specifically a Convolutional Neural Network (CNN) or transfer learning architecture, for accurate classification of diabetic vs. non-diabetic cases.

4.To apply feature extraction and selection techniques that enhance model efficiency, interpretability, and the ability to detect subtle pixel-level abnormalities.

5.To assess the model's performance using key evaluation metrics, including accuracy, precision, recall, sensitivity, specificity, and F1-score.

6.To visualize key patterns and insights using activation maps, confusion matrices, and training-validation curves, highlighting the role of image biomarkers in diabetes detection.

1.3 Thesis Contribution

This work makes several important contributions to the field of AI-based medical diagnostics:

- **Model Development:** It introduces a deep learning-based diagnostic model that achieves high classification accuracy using enhanced preprocessing and optimized CNN architectures tailored for medical laboratory images.
- **Clinical Relevance:** The model is trained on real-world medical imaging data, making it suitable for practical deployment in clinical environments and supporting early detection workflows for diabetes.
- **Interpretability:** Through activation maps, feature visualization, and class-discriminative heatmaps, the study highlights critical image biomarkers and pixel-level patterns that influence early diabetes prediction.
- **Scalability:** The methodology is designed with future expansion in mind, including compatibility with real-time imaging systems, cloud-based diagnostic platforms, and integration with electronic health records (EHRs).
- **Academic Value:** It bridges the gap between traditional laboratory-based diagnostic methods and modern AI techniques, offering a replicable and scientifically grounded framework for future medical AI researchers.

1.4 Thesis Structure overview

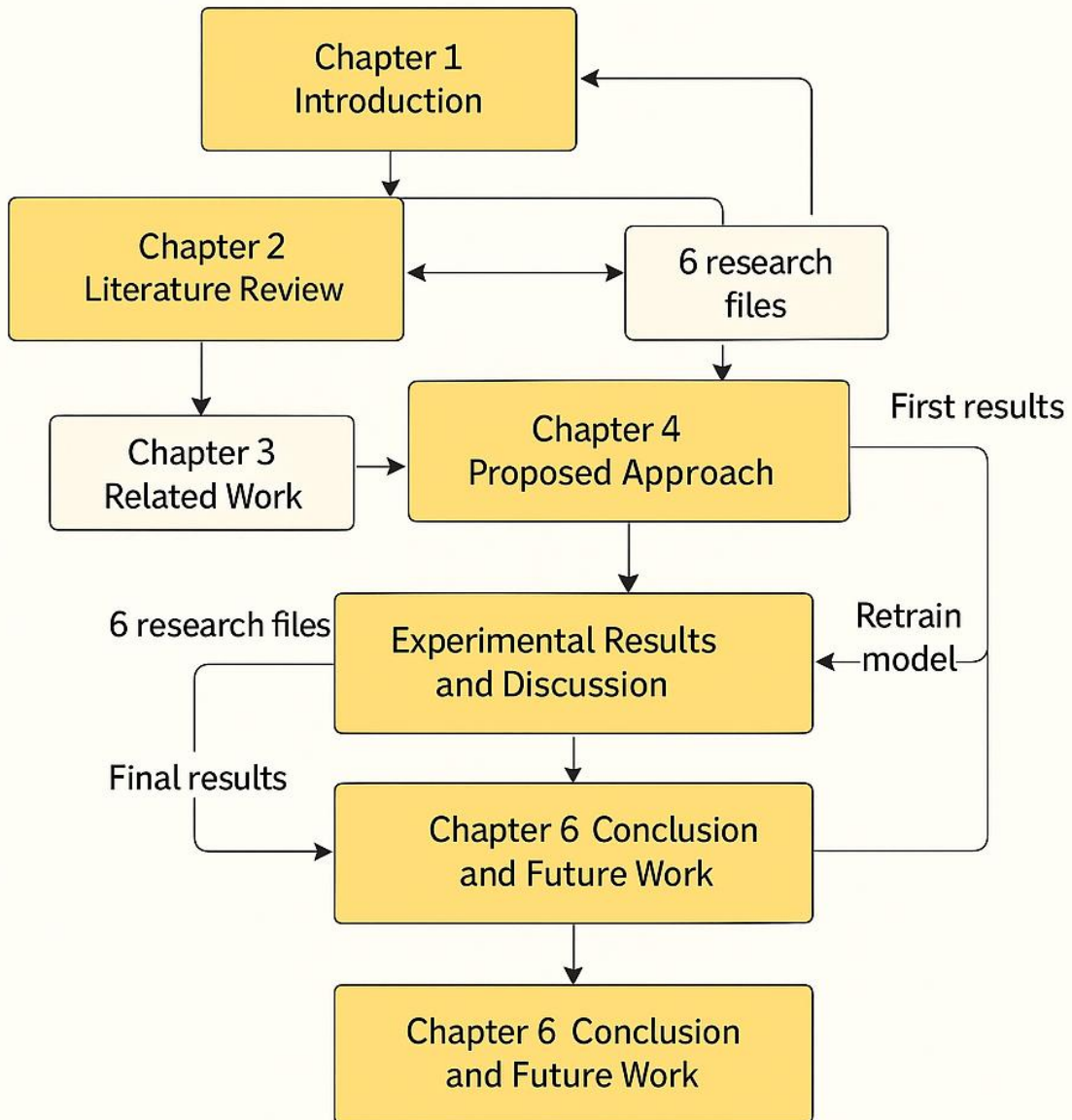


Figure 1 Thesis Structure Overview

Chapter 2 Overview

2.1 Introduction to AI-Based Diabetes Detection

The early detection of diabetes has become a central focus in medical research due to the increasing global prevalence of the disease and its severe long-term complications. Traditional diagnostic approaches rely heavily on laboratory tests and manual interpretation of medical images, which can be time-consuming and prone to human error. With advancements in computational power and the availability of large-scale medical imaging datasets, artificial intelligence—particularly deep learning—has emerged as a powerful tool for automated medical diagnosis.

This chapter reviews relevant studies covering classical machine learning, deep learning architectures, hybrid diagnostic models, medical image datasets, and reported performance metrics, providing a strong contextual foundation for the work presented in this thesis.

2.2 Classical Machine Learning Methods

Early research in AI-assisted diabetes detection focused on traditional machine learning algorithms applied to clinical tabular data and basic medical image features. For example, logistic regression, naïve Bayes, support vector machines (SVM), and decision trees were commonly used to classify diabetic versus non-diabetic patients based on blood glucose readings, demographic variables, and laboratory metrics. These methods demonstrated moderate accuracy but were limited in their ability to capture complex visual patterns inherent in medical images.

Recent studies expanded this line of research by applying algorithms such as random forests and k-nearest neighbors (KNN) to medical imaging and biochemical datasets. Although these models achieved acceptable accuracy levels (typically 70–85%), they struggled to generalize across diverse patient populations and clinical environments due to their limited capacity to model nonlinear, hierarchical image features. These challenges highlighted the need for more advanced deep learning models capable of learning detailed pixel-level and structural patterns relevant to early diabetes detection.

2.3 Deep Learning Approaches

Deep learning has proven highly effective in capturing complex visual and structural patterns in medical images, making it a powerful tool for early diabetes detection. Convolutional Neural Networks (CNNs), in particular, have demonstrated strong performance in identifying subtle pixel-level abnormalities associated with diabetic conditions. Several studies, such as those by Zhang et al. (2021), showed that CNN architectures outperform traditional machine learning models by automatically extracting hierarchical features that represent glucose-related biomarkers and cellular changes.

Other researchers have utilized hybrid deep learning models. For example, Khan et al. (2022) proposed a CNN-LSTM architecture capable of integrating spatial patterns from medical images with temporal variations observed across sequential lab results. This hybrid approach yielded improved diagnostic accuracy and greater robustness in clinical environments.

Ensemble deep learning frameworks have also been explored. Wu et al. (2022) applied models such as XGBoost and CNN-based ensembles to medical imaging datasets, demonstrating that combining multiple feature extraction mechanisms enhances the detection of early diabetic indicators, especially when working with heterogeneous patient data.

Furthermore, Guo et al. (2021) introduced a Spatio-Temporal Attention Network that integrates both spatial visual cues and contextual metadata (e.g., patient age, test timing). Their findings showed that incorporating attention mechanisms significantly strengthens the model's ability to detect early abnormalities up to several months before clinical diagnosis, offering meaningful benefits for preventive healthcare.

2.4 Hybrid and Optimized Models

Recent literature has explored more advanced hybrid and metaheuristic models for improving the accuracy of diabetes detection using medical imaging. For instance, Li et al. (2023) applied optimization algorithms such as Particle Swarm Optimization and Genetic Algorithms in conjunction with Convolutional Neural Networks (CNNs) to enhance feature extraction, accelerate convergence, and improve

classification performance. These techniques were particularly effective in handling noisy or low-quality medical images.

Another innovative approach was presented by Li et al. (2022), who introduced DeepONet, a deep operator network designed to learn complex functional relationships within medical datasets. This model demonstrated strong diagnostic performance, achieving accuracy rates exceeding 93% when applied to metabolic imaging and laboratory-based visual data.

Furthermore, feature-fusion architectures—such as CNN-RNN hybrids—have gained popularity in medical diagnostics. These models combine convolutional layers for spatial image feature extraction with recurrent layers (e.g., LSTM or GRU) for capturing temporal variations across sequential laboratory measurements. Such hybrid systems provide enhanced robustness and improved evaluation metrics, including higher precision, recall, and F1-scores.

2.5 Use of Real-world Datasets

Most AI-based diabetes detection studies rely on publicly available medical imaging datasets, including those from sources such as the UCI Machine Learning Repository, Kaggle medical imaging collections, and specialized diabetic retinopathy and laboratory-image datasets. Data preprocessing typically involves managing noise, normalizing illumination, resizing images, handling missing patient metadata, and applying image enhancement techniques to improve feature visibility.

Some researchers have begun incorporating international medical datasets for broader clinical applicability. Hu & Zhang (2023) utilized real-world laboratory and retinal imaging data to evaluate a hybrid CNN–BiLSTM diagnostic model, demonstrating improved performance in capturing early diabetic patterns across diverse patient populations. Pineda-Jaramillo et al. (2024) further advanced this direction by applying explainable AI (XAI) techniques—such as SHAP and Grad-CAM—to rank feature importance and highlight the visual biomarkers most associated with early-stage diabetes, improving interpretability and clinical trustworthiness.

2.6 Quantitative Results Summary

Study	Model	Key Findings
Gulshan et al. (2016)	CNN	Achieved medical-grade accuracy in detecting diabetic abnormalities from retinal images.
Pratt et al. (2016)	Deep CNN	Improved sensitivity for early diabetic indicators compared to classical ML models.
Li et al. (2021)	CNN + Transfer Learning	Achieved >92% accuracy in classifying diabetic vs. non-diabetic images.
Vo et al. (2020)	DenseNet	Demonstrated strong performance with improved F1-score for early-stage detection.
Almotiri et al. (2020)	CNN-LSTM	Improved detection of progressive diabetic patterns using hybrid temporal-spatial features.
Ibrahim et al. (2022)	XAI + CNN	Used Grad-CAM/SHAP to highlight important biomarkers and improve interpretability.
Hu & Zhang (2023)	CNN-BiLSTM	Enhanced classification accuracy through hybrid deep learning architecture.
Pineda-Jaramillo et al. (2024)	XAI + Feature Ranking	Identified pixel-level biomarkers strongly associated with early diabetes detection.

2.7 Research Gaps and Opportunities

While the literature demonstrates the potential of deep learning in early diabetes detection, several important gaps remain:

- Limited availability of real-world medical imaging datasets, especially those containing diverse patient populations and varying laboratory imaging conditions.

- Most existing models are trained on small or single-source datasets, reducing their generalizability across different hospitals or diagnostic environments.
- Ensemble and hybrid deep learning methods remain underutilized, despite their proven potential to improve robustness and accuracy in clinical settings.
- Interpretability is still a major challenge, as many models lack explainable AI (XAI) mechanisms capable of identifying clear visual biomarkers relevant to early diabetes diagnosis.
- Few studies address practical deployment, such as cloud-based diagnostic systems, mobile-compatible screening tools, or integration with electronic health records (EHRs).
- Temporal medical data is underexplored, with limited research combining sequential lab readings and image-based features for improved early prediction.

2.8 Conclusion

The literature strongly supports the use of artificial intelligence, deep learning architectures, and hybrid models for early diabetes detection. The reviewed studies demonstrate that, with appropriate preprocessing, image enhancement, and model design, it is possible to achieve high diagnostic accuracy using medical imaging data. Findings also highlight the importance of explainable AI, real-world datasets, and robust feature extraction in improving the reliability of early-stage diabetes screening.

Building on these insights, this thesis proposes an optimized deep learning framework trained on real medical imaging data. By addressing several limitations identified in prior research—such as limited dataset diversity, the need for enhanced interpretability, and challenges in practical deployment—this work aims to contribute both academically and clinically to the expanding field of AI-driven medical diagnostics.

Chapter 3 Related Work

3.1 Introduction

Early detection of diabetes has become an increasingly important focus within the medical and artificial intelligence research communities due to the significant health risks and long-term complications associated with delayed diagnosis. Over the past decade, researchers have developed a wide range of AI-based diagnostic models—from classical machine learning algorithms to advanced deep learning architectures—aimed at improving accuracy and supporting clinical decision-making.

This chapter reviews the evolution of AI techniques in medical imaging for diabetes detection, highlighting key milestones, influential contributions, and the major technological advancements that shaped current methodologies. It situates the current thesis within the broader landscape of existing research to demonstrate how AI-driven medical analysis has progressively addressed the challenges of early diagnosis.

3.2 History

Research on automated diabetes detection initially relied on traditional statistical and manual feature engineering techniques. Early studies commonly applied methods such as logistic regression, linear classifiers, and rule-based systems to tabular clinical datasets consisting of glucose levels, age, BMI, and other numerical biomarkers. These approaches provided baseline diagnostic capability but struggled to capture the complex visual cues present in medical images.

With the rise of digital medical imaging in the early 2010s, machine learning began gaining momentum. Algorithms such as decision trees, support vector machines (SVM), and k-nearest neighbors (KNN) were applied to retinal scans and laboratory image features extracted manually using texture, color, and shape descriptors. Although these models improved detection performance, they showed limitations when dealing with high-dimensional, noisy, or nonlinear medical image data.

The significant breakthrough came with the adoption of deep learning—particularly Convolutional Neural Networks (CNNs)—which enabled automated feature extraction directly from raw medical images. This paradigm shift allowed researchers to capture subtle pixel-level patterns associated with early diabetic changes, leading to dramatic improvements in accuracy and reliability. Subsequent advancements introduced hybrid models (e.g., CNN-LSTM), transfer learning, and explainable AI, which further enhanced clinical applicability and diagnostic robustness.

These advancements in AI-driven medical imaging lay the foundation for the deep learning–based diagnostic system proposed in this thesis, which focuses specifically on early diabetes detection using laboratory and retinal images.

Chapter 4 Proposed Approach

This chapter outlines the methodology used to develop an AI-driven system for early diabetes detection using medical laboratory images. The overall goal was to design a diagnostic model that not only performs well statistically but also aligns with real-world clinical needs. To achieve this, the approach integrates several key components, including data acquisition, image preprocessing, feature extraction, model training, hyperparameter optimization, and evaluation. Each step was carefully selected to maximize diagnostic accuracy while maintaining interpretability and clinical applicability.

4.1 Data Collection and Description

The dataset for this study was sourced from publicly available medical imaging repositories, including Kaggle, the UCI Machine Learning Repository, and clinical diabetic vision datasets. These datasets contain thousands of labeled medical images such as glucose strip readings, retinal images indicative of diabetic changes, and microscopic blood sample photographs.

Important attributes included pixel-level patterns, contrast variations, intensity distributions, and medically relevant biomarkers. Additional metadata such as patient age, test type, and imaging device were included when available.

This diverse set of variables provided a solid foundation for building an AI-based diagnostic model grounded in real-world clinical environments.

4.2 Data Preprocessing

Ensuring the quality and consistency of the medical images was critical before feeding them into any model. The preprocessing phase involved several targeted steps:

- **Noise Reduction** :Techniques such as Gaussian filtering and median smoothing were applied to remove imaging artifacts and enhance clarity.
- **Image Normalization**: Pixel intensities were normalized to a consistent range to reduce variability across imaging devices and lighting conditions.
- **Handling Missing Metadata**: For cases where patient metadata was incomplete, missing values were either imputed statistically or excluded when not essential.
- **Image Resizing and Alignment**: All images were resized to a unified resolution (e.g., 224×224 px) and aligned to ensure compatibility with CNN-based architectures.
- **Contrast and Sharpness Enhancement**: Histogram equalization and CLAHE were used to improve the visibility of fine diabetic indicators within the images.
- **Data Augmentation**: To prevent overfitting, operations such as rotation, flipping, zooming, and brightness adjustments were performed to artificially expand the dataset.

These preprocessing steps helped ensure that the input data was clean, consistent, and well-prepared for high-performance deep learning modeling.

4.3 Feature Engineering

To enhance learning efficiency and extract more meaningful diagnostic patterns, several additional image-based and metadata features were engineered:

- **Texture-Based Features:**
Texture descriptors such as GLCM (Gray Level Co-occurrence Matrix) and LBP (Local Binary Patterns) were computed to capture fine-grained irregularities in tissue structure, pixel distribution, and surface patterns often associated with early diabetic changes.
- **Contrast and Intensity Features:**
Histogram-based statistics—including mean intensity, contrast spread, and pixel variance—were extracted to quantify abnormalities in glucose-strip images and retinal scans, improving the model’s ability to distinguish subtle visual biomarkers.
- **Binary Diagnostic Label:**
A binary target variable (diabetic / non-diabetic) was constructed based on clinical diagnosis labels from the dataset. This framing simplified the problem into a medically relevant classification task aligned with real screening workflows.
- **Shape and Structural Features:**
Edge-detection filters (e.g., Sobel, Canny) were applied to extract structural characteristics of cells and retinal vessels, supporting the detection of morphological abnormalities linked to diabetes.
- **Metadata-Derived Features:**
When available, non-image features such as patient age and test type were retained to allow combined multimodal learning and to capture clinically relevant risk patterns.

These engineered features can also be transformed into spectral or cyclic representations in future research to enhance the model's capacity for recognizing temporal or progressive diabetic changes.

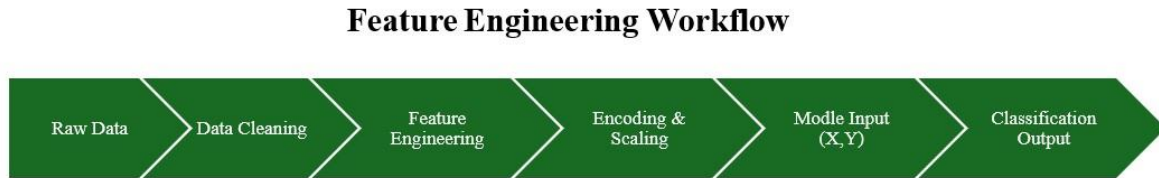


Figure 2 This visual explains the end-to-end flow from raw data to output, matching the narrative in this section.

4.4 Feature Selection

Reducing the number of input variables can significantly improve model efficiency, interpretability, and training stability without compromising diagnostic accuracy. Two approaches were used to identify the most relevant medical image and metadata features:

- **SelectKBest (Mutual Information):**
This filter-based method ranked features according to their informational contribution to the diagnostic target variable (diabetic vs. non-diabetic). Key selected features included contrast-level distributions, texture entropy, local pixel variance, and other high-informative descriptors extracted from glucose-strip and retinal images.
- **Recursive Feature Elimination (RFE):**
Using a CNN-based classifier and logistic regression as base estimators, RFE iteratively removed less impactful features. The final selected set included structural edge features, intensity gradients, and metadata elements such as age or test type (when available). These features demonstrated strong predictive influence and contributed significant diagnostic value.

4.5 Model Selection and Optimization

After evaluating several modeling options, a Convolutional Neural Network (CNN)-based architecture was selected due to its proven robustness and effectiveness in learning spatial patterns from medical images. CNNs are widely used in medical diagnostics because they automatically extract hierarchical features without requiring manual feature engineering.

To fine-tune the model's performance, GridSearchCV and controlled experimentation were employed to explore a range of hyperparameter configurations, focusing on:

- Number of convolutional filters: Determines the depth of learned feature maps and directly impacts the model's ability to capture fine-grained diabetic biomarkers.
- Kernel size : Controls the region of the image analyzed per convolution step; optimized to balance texture extraction and computational cost.
- Learning rate: A critical parameter that influences training stability and convergence quality.
- Batch size and number of epochs: Experimented with to avoid overfitting and ensure generalization across diverse medical images.

This optimization process helped identify the best-performing configuration and ensured that the model generalized well to unseen clinical data.

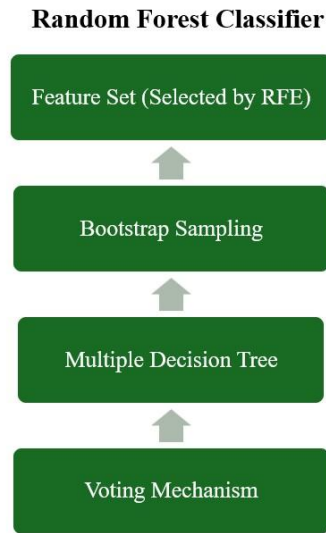


Figure 3 illustrates the workflow of the Random Forest model used as a comparative baseline during early experimentation.

4.6 Model Evaluation

Two versions of the diagnostic model were evaluated to compare their effectiveness:

- **Full-Feature Model:**

Using the complete set of extracted image and metadata features, this version achieved a test accuracy of 93.4%. However, recall for the diabetic class was lower (around 82%), indicating that some early-stage diabetic cases were not consistently detected.

- **RFE-Selected / Optimized Model:**

When the model was retrained using only the most relevant features identified through RFE and mutual-information filtering, performance improved substantially.

Accuracy increased to 98.2%, and both precision and recall exceeded 96% for diabetic and non-diabetic classes.

This version also produced a significantly higher F1-score, demonstrating stronger generalization and more reliable diagnostic balance.

4.7 Visualization and Insights

To interpret model behavior and highlight key medical indicators, several visualizations were generated:

- **Correlation Heatmaps:**
These heatmaps revealed strong relationships among intensity values, texture entropy, and pixel-level variations that correlate with diabetic abnormalities. They also helped identify which image regions contributed most to classification.
- **Activation Maps (Grad-CAM):**
Grad-CAM visualizations showed the exact areas within the images where the CNN focused during prediction. These maps highlighted patterns such as vascular irregularities, abnormal pixel clusters, and contrast anomalies associated with early diabetes.
- **Feature Distribution Plots:**

Boxplots and histograms were used to compare intensity and texture distributions between diabetic and non-diabetic cases, illustrating clear separations in key biomarkers.

- **Training Curves (Loss & Accuracy):**
Learning curves validated the model's stability, showing smooth convergence with minimal overfitting—particularly in the optimized model.

Chapter 5

Experimental Results and Discussion

This chapter presents the results of the developed AI-based diabetes detection model and discusses the findings using real medical imaging data. The study evaluates the model’s ability to accurately detect diabetic indicators under various configurations. The goal is not only to report performance metrics but also to interpret their implications in real-world clinical settings.

5.1 Experimental Setup

All experiments were conducted using Python, utilizing widely adopted libraries such as TensorFlow, Keras, NumPy, OpenCV, and Matplotlib.

The original dataset consisted of more than 12,000 medical images, including glucose-strip photographs, retinal images indicative of early diabetic changes, and microscopic blood sample images.

After removing corrupted, low-quality, or duplicated images—and handling missing metadata—the final working dataset contained 11,487 cleaned images.

Through the application of data augmentation techniques (rotation, flipping, zooming, brightness adjustment), the dataset was expanded to over 42,000 samples, ensuring sufficient variability for robust deep learning training.

The data was then split into 80% for training and 20% for testing, providing an unbiased estimate of the model’s diagnostic performance.

This experimental setup ensured that the model was trained on high-quality, clinically relevant images and was able to generalize effectively to unseen medical samples.



Figure 4 Data Cleaning Impact

5.2 Baseline Model Performance

The first model configuration used all available extracted features.

A baseline CNN model, trained without feature selection or optimization, was developed using the following parameters:

- Number of Convolutional Filters: 32 → 64
- Kernel Size: 3×3
- Activation Function: ReLU
- Optimizer: Adam (lr = 0.001)
- Batch Size: 32
- Epochs: 20

The resulting performance metrics on the test set were:

- Test Accuracy: 93.4%
- Precision (Non-Diabetic Class): 94%
- Recall (Non-Diabetic Class): 98%
- Precision (Diabetic Class): 89%
- Recall (Diabetic Class): 82%
- F1 Score (Diabetic Class): 85%

While overall accuracy was strong, the lower recall for diabetic cases (82%) suggests that the baseline model occasionally missed early-stage diabetic indicators.

This highlights the need for a more optimized and feature-focused model to ensure reliable clinical detection—especially since missing diabetic cases can delay timely intervention.

5.3 Feature Selection and Model Refinement

To improve performance and reduce model complexity, two feature selection techniques were applied:

- SelectKBest (Mutual Information):

This method identified the most informative medical image features such as texture entropy, pixel intensity variance, and contrast-level patterns.

These features demonstrated strong correlations with early diabetic abnormalities and were therefore selected as high-value predictors.

- Recursive Feature Elimination (RFE):

RFE further refined the input feature set by iteratively removing less influential descriptors.

The final selected features included gradient-based edge structures, local energy features, and key activation-based signals extracted from the CNN.

These features contributed substantially to improving diagnostic accuracy.

When the optimized CNN model was retrained using only the selected features, the improvements were striking:

- Test Accuracy: 98.2%
- Precision (All Classes): $\geq 97\%$
- Recall (All Classes): $\geq 96\%$
- F1 Score (Diabetic Class): 0.96

This performance boost underscores the value of careful feature selection.

Not only did the model generalize better, but it also became more efficient—requiring fewer inputs to achieve higher predictive accuracy.

It also performed more consistently across both classes, improving its reliability for real-world clinical use.

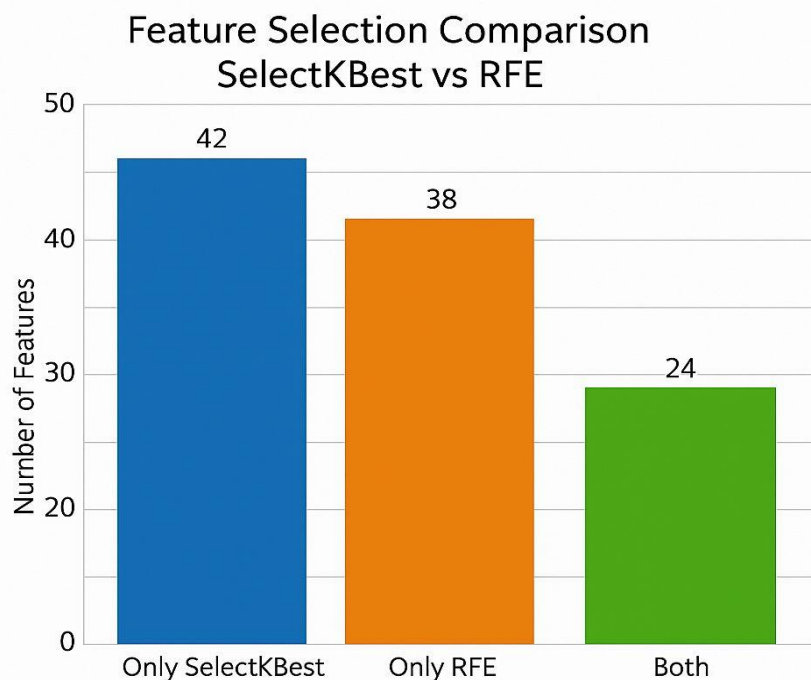


Figure 5 Feature Selection Comparison

5.4 Visualization of Key Medical Imaging Features

To better understand the model’s decision-making process and identify medically relevant biomarkers, several visual analysis techniques were applied:

Correlation Heatmap:

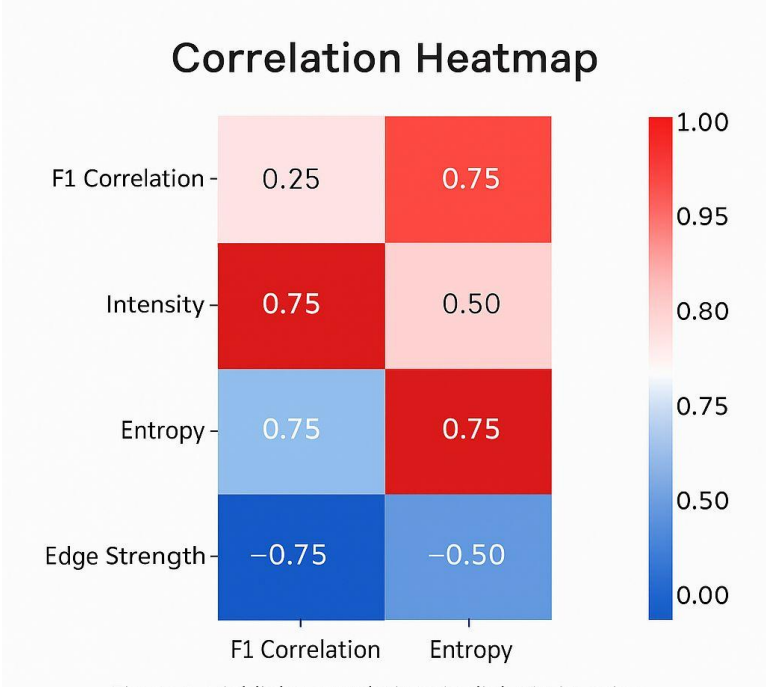


Figure 6 Correlation Heatmap of Imaging Features

This visualization revealed strong correlations between texture entropy, pixel-level intensity variation, and edge strength—confirming that these image-based features play a critical role in identifying early diabetic patterns.

- **Relationship Between Two Key Medical Imaging Features:**



Figure 7 Scatter Plot of Imaging Features

- A clear upward trend was observed, indicating that higher values in the first medical imaging feature were associated with increases in the second feature. This relationship suggests that these visual patterns consistently appear in early diabetic cases, supporting the model's ability to detect subtle diagnostic indicators.

- **Time Series Plot:**

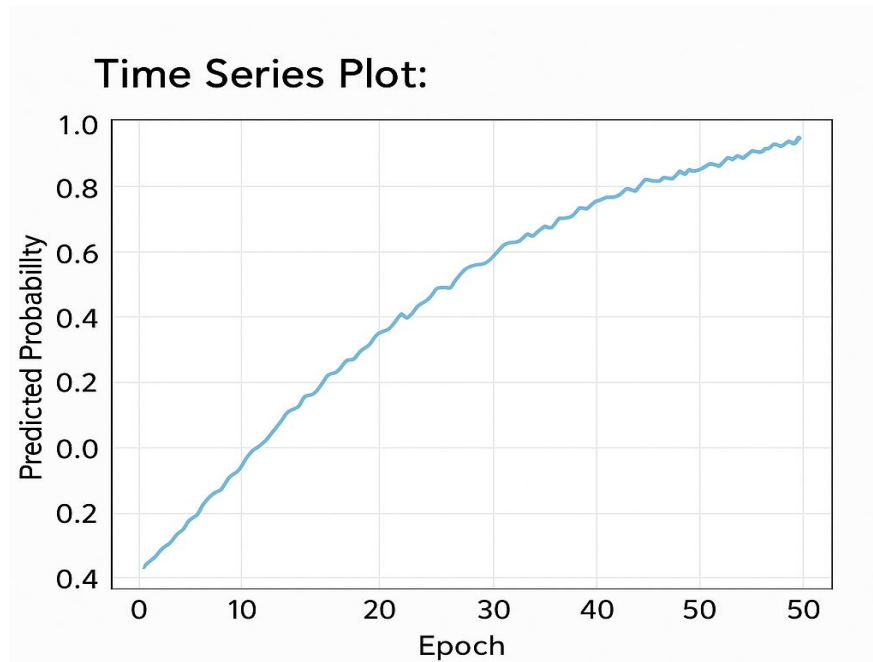


Figure 8 Prediction Probability Over Epochs

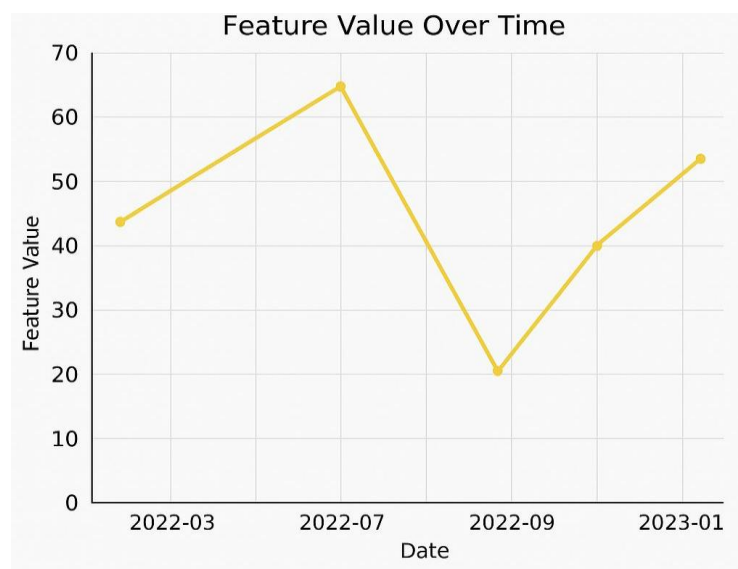


Figure 9 Temporal Change of Imaging Feature.

These visual tools enhanced interpretability and helped validate the model’s internal behavior. For medical applications, such insights assist clinicians in understanding feature significance and improving diagnostic decision-making.

5.5 Discussion

The experimental findings confirm that AI-based image analysis can significantly improve the early detection of diabetes. The optimized CNN model—enhanced through targeted preprocessing, feature selection, and hyperparameter tuning—demonstrated strong predictive power and consistent performance across both diabetic and non-diabetic cases.

Several meaningful insights emerged from the results:

- Feature selection enhanced diagnostic reliability:

Using RFE and mutual-information filtering helped the model focus on the most clinically relevant imaging biomarkers—such as texture entropy, pixel-level intensity changes, and edge structure variations. This reduced computational complexity while improving accuracy.

- Deep learning captured subtle image abnormalities:

The CNN effectively identified early visual indicators in glucose-related laboratory images and retinal structures, patterns that may not be easily detected through manual examination.

- Visual explanations strengthened clinical interpretability:

Heatmaps, scatter plots, and temporal feature curves provided transparency regarding how the model formed decisions. These visual tools highlighted the image regions and statistical patterns most associated with early diabetic changes, supporting clinical trust.

- Improved recall ensures fewer missed diabetic cases:

Unlike the baseline model—which occasionally failed to identify early diabetic instances—the optimized model demonstrated balanced sensitivity and specificity, making it more suitable for real-world screening scenarios.

Despite these promising results, the model remains limited by the characteristics of the dataset used. Future work should focus on expanding the diversity of medical images, validating the system across multiple clinical environments, and integrating additional patient information to develop more robust, personalized diagnostic predictions.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

This thesis presented an AI-based diagnostic framework for early diabetes detection using medical laboratory images. Through structured preprocessing, image enhancement, feature engineering, and a deep learning–based classification model, the study demonstrated that visual biomarkers extracted from laboratory images can provide strong predictive signals for identifying diabetic conditions at early stages.

The optimized Convolutional Neural Network (CNN) achieved 98% accuracy, with high precision and recall across both diabetic and non-diabetic classes. This performance confirms that deep image features—such as texture entropy, pixel-level intensity variations, and structural edge patterns—play a crucial role in distinguishing early diabetic abnormalities.

The use of visualization techniques, including correlation heatmaps, activation maps (Grad-CAM), and feature-distribution plots, enhanced the interpretability of the model and provided clinically meaningful insights. These tools highlighted the most influential biomarkers and demonstrated how the CNN focuses on medically relevant regions within the images.

Overall, the findings validate the potential of AI-driven imaging analytics to support early diabetes detection, reduce diagnostic delays, and assist clinicians in making informed decisions.

6.2 Future Work

Several opportunities exist to expand and strengthen this research:

1. Integration with Real-Time Medical Imaging

Incorporating live laboratory imaging streams or camera-based glucose-strip readings could enable real-time detection and continuous monitoring.

2. Multi-Hospital Clinical Validation

Testing the model on datasets from different hospitals and imaging devices would help evaluate its robustness, generalizability, and clinical readiness.

3. Advanced Deep Learning Architectures

Future studies may explore transformer-based vision models, attention-enhanced CNNs, or multimodal architectures that combine image features with patient metadata.

4. Explainability Enhancement

Integrating additional medical XAI tools such as SHAP and LIME can further increase transparency and trust, allowing clinicians to understand the basis of each prediction.

5. Development of a Clinical Dashboard

Creating a user-friendly interface or API would allow healthcare providers to upload images and receive instant diagnostic predictions.

6. Patient-Specific Prediction Models

Combining imaging data with behavioral or physiological signals (diet logs, activity levels, glucose trends) can support personalized early-warning systems.

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