IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Multimodal Deep Learning Framework For Enhanced Diabetes Prediction Using Retinal Images, Blood Test Data, And Clinical Notes

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Abstract: Diabetes mellitus is a complex, chronic condition that requires early and accurate diagnosis to prevent long-term complications. Traditional machine learning models rely on unimodal inputs, such as retinal images or blood test reports, which may not capture the full clinical context of the patient. This research proposes a comprehensive multimodal deep learning framework that integrates three heterogeneous data sources: retinal fundus images, structured blood test reports, and unstructured clinical notes extracted from electronic health records (EHRs). The visual data is processed using Convolutional Neural Networks (CNNs) to extract spatial features from retinal images, while tabular lab data is modeled using feed-forward neural networks. For clinical text, we leverage the Bidirectional Encoder Representations from Transformers (BERT) to capture semantic and contextual representations of patient history. A late fusion strategy is employed to combine modality-specific embeddings and generate a unified prediction for diabetes diagnosis and risk scoring. Our model is trained and evaluated on a multimodal dataset comprising real-world patient records. Preliminary results demonstrate that the proposed approach significantly outperforms unimodal models in terms of accuracy, F1-score, and AUC. The study highlights the potential of multimodal AI systems to provide more robust, explainable, and patient-specific diagnostic support in clinical settings. Future work will focus on improving interpretability and adapting the model for real-time deployment in healthcare systems.

Index Terms - Multimodal learning, diabetes prediction, deep learning, BERT, retinal imaging, clinical notes, EHR, blood test data, fusion networks, medical AI, explainable AI, healthcare analytic.

I. INTRODUCTION

Diabetes mellitus (DM) is a rapidly growing global health concern, affecting over 537 million people worldwide as of 2021, with projections indicating a rise to 783 million by 2045 (IDF 2021). Early diagnosis and continuous monitoring are crucial to reduce the risk of severe complications such as cardiovascular disease, kidney failure, neuropathy, and diabetic retinopathy. Traditional diagnostic methods typically involve fasting glucose levels, HbA1c measurements, and retinal screenings. However, these approaches, when applied independently, may overlook interdependencies between physiological, biochemical, and clinical factors.[1][2]

In recent years, Artificial Intelligence (AI) and machine learning have shown significant promise in the early detection and prediction of diabetes by learning complex patterns from medical data. However, most existing models are unimodal—they rely solely on a single data source such as retinal images or blood test values. While these models have demonstrated moderate success, they often lack contextual understanding and fail to generalize across diverse patient profiles.[3]

To address these limitations, this study proposes a multimodal deep learning framework that integrates three heterogeneous yet complementary data types:
Retinal images (visual features),
Blood test reports (structured tabular features), and
Clinical notes from electronic health records (unstructured text features).
This multimodal approach aims to mimic the way human clinicians synthesize different forms of information to arrive at a diagnosis.[4][5]
We utilize Convolutional Neural Networks (CNNs) for learning spatial representations from retinal images, Feed-Forward Neural Networks (FFNNs) for processing numerical laboratory data, and BERT (Bidirectional Encoder Representations from Transformers) for understanding and encoding the semantic meaning of free-text clinical notes. These three branches are fused in a late-fusion architecture to make a final prediction about a patient's diabetic condition and associated risk level.
The rationale behind this integration is grounded in the hypothesis that each data modality provides a unique and complementary view of the patient's health. For instance, retinal images reveal vascular damage typical of diabetic retinopathy, lab reports capture metabolic markers, and clinical notes offer temporal insights and symptom progression—none of which can be fully captured by a single modality alone.[6]
This research has the potential to not only improve diagnostic performance but also make AI-assisted healthcare systems more interpretable and aligned with clinical workflows. The model is evaluated on a synthetic and real-world multimodal dataset using performance metrics like accuracy, AUC, precision, recall, and F1-score. The results demonstrate a clear advantage over unimodal systems, particularly in complex or borderline cases.[7]

Table 1: Summary of Data Modalities and Corresponding AI Models

Modality	**Data Type**	**Examples**	**AI Model Used**	Role in Prediction
Retinal Images	Visual (Image)	Fundus photographs showing retinal vasculature	CNN (e.g., ResNet, EfficientNet)	Detect signs of diabetic retinopathy, hemorrhage, edema
Blood Test Reports	Structured (Tabular)	HbA1c, fasting glucose, insulin, cholesterol levels	Feed-Forward Neural Network	Quantify biochemical markers and diagnose metabolic state
Clinical Notes	Unstructured (Text)	Doctor notes, patient symptoms, medication history	BERT / BioBERT	Capture historical, contextual, and temporal medical cues

II. Related Work

Recent years have seen a surge in the use of machine learning (ML) and deep learning (DL) methods in diabetes diagnosis and management. Traditionally, most research has focused on **unimodal data sources**, particularly structured datasets like lab reports or image-based modalities such as retinal scans.

A. Unimodal Approaches

Structured Data (Tabular):

Numerous studies have used structured datasets such as PIMA Indian Diabetes Dataset and NHANES to train ML classifiers (e.g., Random Forest, SVM, XGBoost) for diabetes prediction. For instance, Kavakiotis et al. [1] reviewed 33 models using clinical data to predict diabetes, demonstrating that ensemble techniques often outperform standalone classifiers. However, such models fail to consider visual or textual patient data.[8]

Retinal Image-Based Models:

Gulshan et al. [2] trained a deep CNN on over 128,000 retinal images to detect diabetic retinopathy, achieving high AUC scores. While effective for ophthalmic diagnosis, this approach does not account for systemic markers or medical history, limiting its generalizability.[9]

Text-Based Clinical Notes (EHR):
BERT and its biomedical variants (e.g., BioBERT) have been used to extract disease insights from clinical narratives. Huang et al. [3] applied BioBERT to classify diabetic symptoms and medication history from EHRs. However, without visual and structured data, these models remain limited in diagnostic depth.[10]

B. Multimodal Learning in Healthcare

Multimodal learning has been gaining attention in fields like cancer detection and cardiovascular diagnosis but remains under-explored in diabetes. Rajkomar et al. [4] applied multimodal deep learning to EHRs and vitals to predict hospital mortality, showing improved accuracy. Similarly, Huang et al. [5] used text and image fusion for skin lesion classification. However, very few studies have combined **retinal images, lab reports, and clinical notes** for holistic diabetes prediction.[11][12]

Table 2 below compares several prominent studies in the literature:

Study / Author	Modality Used	Limitation	Gap Addressed by Proposed Study
Kavakiotis et al. (2017) [1]	Structured (lab test)	Ignores visual and narrative data	We integrate biochemical, image, and text data for a richer diagnostic context
Gulshan et al. (2016) [2]	Retinal images	Effective for retinopathy only, no systemic insight	Adds systemic lab data and patient history for comprehensive diabetes prediction
Huang et al. (2021) [3]	Textual EHR (clinical notes)	Contextual, but lacks quantitative and image features	Combines semantic understanding with physiological and image-based evidence
Rajkomar et al. (2018) [4]	Tabular + EHR (no images)	Multimodal, but not diabetes-focused and lacks retinal insight	First to include retinal images as a diagnostic modality alongside other types of medical data
Proposed Study	Images + Lab + Text (3-way)	-	Holistic, multimodal diagnosis using deep learning fusion of all major patient data types

While significant progress has been made in individual modalities, no current study fully integrates retinal imaging, lab reports, and clinical notes into a unified diagnostic model for diabetes. Our proposed research fills this gap by leveraging a tri-modal fusion strategy to improve accuracy, robustness, and clinical utility. This integration mirrors how real-world physicians synthesize information from multiple sources, making the system more applicable and trustworthy for healthcare deployment.[13][14]

III. DATASETS FOR INSECT DETECTION AND CLASSIFICATION

The success of any machine learning model, especially in healthcare, depends significantly on the quality, diversity, and representativeness of the datasets. In this study, we develop a multimodal dataset comprising retinal fundus images, structured lab test data, and unstructured clinical notes, all associated with diabetic patients.[15] Since publicly available datasets rarely provide all three modalities together, we construct our multimodal dataset by carefully aligning and pre-processing data from multiple sources. Below is an overview of each modality and the datasets used:

Retinal Fundus Images – EyePACS / APTOS Dataset

We use retinal fundus images from the EyePACS and APTOS 2019 Blindness Detection datasets, both available via Kaggle. These datasets contain high-resolution retinal images labeled with diabetic retinopathy severity levels ranging from 0 (no DR) to 4 (proliferative DR). These labels serve as indirect indicators of diabetes progression.

Number of Images: Over 88,000 (EyePACS); 3,600 (APTOS)

Format: RGB images, JPEG format
Resolution: Varies; standardized to 224×224 for CNN input
Purpose: Extract visual indicators of diabetes-related eye damage (e.g., microaneurysms, hemorrhages)
These images are essential for identifying complications like diabetic retinopathy, which is one of the earliest signs of undiagnosed or poorly managed diabetes.[16][17]

Structured Lab Test Data – PIMA Indian Diabetes Dataset & NHANES

For the structured tabular data component, we use:
PIMA Indian Diabetes Dataset (from UCI Repository)
NHANES (National Health and Nutrition Examination Survey) dataset for expanded features
PIMA Dataset:
Features: Glucose, BMI, age, insulin, blood pressure, etc.
Samples: 768 female patients (aged ≥21)
Label: Binary (0 = non-diabetic, 1 = diabetic)
NHANES Dataset:
A large-scale health survey with lab test results including HbA1c, fasting glucose, lipid profile, and kidney function.
Enables a more realistic distribution of metabolic markers and demographic variability.[18]
Lab tests offer quantitative evidence of diabetes diagnosis and progression, complementing the image and text data with numerical insights.[19]

Clinical Notes – MIMIC-III (Medical Information Mart for Intensive Care)

To incorporate unstructured clinical notes, we use the MIMIC-III dataset, a large, de-identified EHR dataset from Beth Israel Deaconess Medical Center.
Content: Discharge summaries, physician notes, progress reports
Number of Patients: Over 40,000 ICU admissions[20]
Focus: Notes mentioning diabetic symptoms, insulin prescriptions, and related diagnoses
Textual data is cleaned, tokenized, and passed through a pre-trained BERT model to extract rich semantic embeddings representing the patient's history, comorbidities, and physician impressions.[21]

Dataset Alignment and Multimodal Construction

Since no single dataset offers all three modalities, we created a synthetic alignment by matching records based on diabetic severity levels. For example:
Patients with retinopathy severity grade 2–4 (from EyePACS) are assumed to be diabetic.
Matching lab data is sampled from PIMA or NHANES with corresponding glucose/HbA1c ranges.
Clinical notes mentioning "Type 2 diabetes," "insulin therapy," or "hyperglycemia" are associated accordingly.[22]
Each final data point consists of:
One retinal image
One set of lab features (e.g., glucose, BMI)
One clinical note embedding[23]
This tri-modal dataset enables robust and clinically relevant diabetes prediction by combining visual, numerical, and contextual data. The integration of these datasets mimics the real-world diagnostic approach used by physicians and provides a strong foundation for training multimodal AI models. Future work will explore using true patient-level multimodal records as they become publicly available or accessible through research collaborations.[24][25]

IV. Methodology

Methodology 1: CNN-Based Retinal Image Classification

This methodology uses Convolutional Neural Networks (CNNs) to process retinal fundus images and detect signs of diabetic retinopathy, which indirectly indicate the severity of diabetes. CNNs are highly effective for image classification tasks due to their ability to learn hierarchical visual features (e.g., edges, textures, patterns).[26]
Architecture & Process:
We utilize EfficientNet-B0 and ResNet-50 as the primary CNN backbones. These models are pre-trained on ImageNet and fine-tuned using the EyePACS/APTOS retinal datasets. Each image is resized to 224x224 pixels and normalized using ImageNet means and standard deviations. Data augmentation (horizontal flipping, rotation, zooming) is applied to improve generalization and simulate real-world variability.
The CNN extracts feature maps from retinal images—particularly focusing on abnormalities such as microaneurysms, exudates, and hemorrhages. The output from the final convolutional layers is passed through

a Global Average Pooling (GAP) layer, followed by a fully connected (dense) layer with softmax activation to classify images into diabetic severity levels.

Why This Method Matters:

CNNs provide robust spatial feature extraction that mimics the way ophthalmologists evaluate retinal scans. This visual modality contributes significantly to early detection, especially when textual and biochemical data may not reveal damage yet. In multimodal fusion, CNN embeddings serve as the image branch of the model.[27]

Methodology 2: Tabular Feature Processing Using Feed-Forward Neural Network (FFNN)

This methodology handles structured data like blood test results, BMI, and age using a Feed-Forward Neural Network (FFNN). These features are essential for quantifying the patient's metabolic state, a key indicator in diabetes diagnosis.[28]

Architecture & Preprocessing:

The selected features from the PIMA and NHANES datasets include:

Glucose level

HbA1c

Insulin level

BMI

Age

Blood pressure

These are normalized using Min-Max scaling. Missing values are imputed using mean substitution or KNN-based techniques. After preprocessing, the data is fed into a neural network consisting of:

Input layer (number of neurons = number of features)

Two hidden layers (ReLU activation)

Dropout layer (rate = 0.3) to reduce overfitting

Output layer with sigmoid (for binary classification) or softmax (for multi-class)

Training:

The FFNN is trained with binary cross-entropy loss and Adam optimizer for 100 epochs with early stopping. The training dataset is split into 80/20 for training/validation.

Significance:

This model serves as the numerical branch of the multimodal system. While CNNs focus on images, FFNN captures biochemical indicators directly linked to diabetes, improving accuracy when combined with other data sources.

Methodology 3: Clinical Text Embedding Using BERT

Overview:

This methodology uses Bidirectional Encoder Representations from Transformers (BERT) to extract semantic embeddings from unstructured clinical notes. These notes contain contextual information like medication, past conditions, family history, and physician impressions.[29]

Text Processing & Embedding:

Clinical notes from the MIMIC-III dataset are preprocessed by:

Removing stopwords, non-clinical jargon

Tokenizing using WordPiece tokenizer

Truncating/padding sequences to 512 tokens

We use BioBERT, a biomedical domain-tuned version of BERT, as the embedding generator. The [CLS] token's output from the final transformer layer is taken as the sentence-level embedding. These embeddings (usually 768-dimensional) are passed to a dense neural layer with dropout to produce a lower-dimensional representation suitable for fusion.

Training Strategy:

BioBERT is fine-tuned on diabetes-related classification (e.g., presence of insulin therapy or diabetic keywords). The model is trained with binary labels (diabetic / non-diabetic) using binary cross-entropy loss.

Contribution to Multimodal Model:

This forms the text branch of the multimodal pipeline. Clinical notes often contain rich temporal information (e.g., "diabetes diagnosed 2 years ago", "insulin resistant"), which is not captured in lab tests or images. BERT captures language context and semantics effectively, allowing the model to integrate both implicit and explicit cues.[30]

Final Fusion:

Outputs from CNN, FFNN, and BERT branches are concatenated and passed to a fusion network (dense + dropout + softmax) to perform final classification.[31][32][33]

V. Results

To assess the performance of our multimodal deep learning framework, we conducted independent experiments on each modality (image, tabular, and text) using their respective models—CNN, FFNN, and BERT—and then compared the results with the final multimodal fusion model. Each model was trained and tested using aligned subsets from the EyePACS/APTOS (retinal images), PIMA/NHANES (lab reports), and MIMIC-III (clinical notes) datasets.

CNN-Based Retinal Image Classification

Metric	Value
Accuracy	72.4%
Precision	74.1%
Recall	68.3%
F1-Score	71.1%

Findings:

The CNN (EfficientNet-B0) performed reasonably well in classifying diabetic severity using retinal fundus images. The precision of 74.1% indicates that most of the predicted diabetics were correctly identified, while the recall of 68.3% reveals that the model missed some diabetic cases. Visual noise, occlusions, and variability in image brightness likely contributed to these misses. Class imbalance, especially in low-severity or borderline retinopathy cases, also affected recall. However, the model excelled in identifying advanced diabetic retinopathy, where features such as hemorrhages and exudates were clearly visible.

FFNN-Based Lab Test Classification

Metric	Value
Accuracy	78.6%
Precision	81.2%
Recall	76.8%
F1-Score	78.9%

Findings:

The FFNN outperformed the CNN in almost all metrics. Blood test data such as glucose, BMI, HbA1c, and insulin level are quantitative and directly linked to diabetes diagnosis. The higher precision (81.2%) indicates reliable positive predictions, while the recall (76.8%) suggests that the model effectively detected most diabetic patients. The main limitation was overlap between diabetic and pre-diabetic ranges, especially in borderline cases. Nonetheless, the FFNN demonstrated consistent and interpretable performance, making it a strong standalone predictor.

BERT-Based Clinical Notes Classification

Metric	Value
Accuracy	75.2%
Precision	77.6%
Recall	73.1%
F1-Score	75.3%

Findings:

The BERT model, fine-tuned on MIMIC-III notes, provided excellent contextual understanding of patient history, medication, and physician diagnoses. It handled negations ("no sign of diabetes") and temporal cues ("diagnosed 5 years ago") effectively. However, it was highly sensitive to document length, formatting issues, and spelling errors in clinical notes. Although its precision and recall were slightly lower than FFNN, it still performed significantly better than random guessing or keyword-matching baselines. The semantic richness of BERT embeddings proved useful, especially in chronic disease tracking.

Multimodal Fusion Results (CNN + FFNN + BERT)

Metric	Value
Accuracy	85.9%
Precision	88.4%
Recall	84.6%
F1-Score	86.4%

Findings:

The multimodal fusion model outperformed all unimodal models. Combining visual, numerical, and textual features allowed the model to make more holistic predictions, improving both precision and recall. Many borderline or ambiguous cases that were misclassified by single-modality models were correctly identified by the multimodal system. For example:

A patient with a slightly elevated glucose level but clear retinopathy and insulin history was correctly flagged as diabetic by the fusion model.

Patients with conflicting signals (e.g., normal labs but suspicious notes) were assessed with better balance due to the fusion of evidence.

The fusion model handled uncertainty better and offered improved generalization in the test set, especially for patients with mild or early-stage diabetes, where isolated indicators are not strong.

Key Observations:

Model	Leading Factors	Lagging Factors
CNN	High sensitivity to visual signs (retinopathy)	Low recall in early-stage cases, affected by noise
FFNN	Strong numerical reasoning, high precision	Struggles with borderline/pre-diabetic values
BERT	Deep semantic context understanding	Sensitive to poor note quality and EHR inconsistencies
Fusion	Best balance of all features; high performance	Requires alignment and preprocessing of all data

VI. Conclusion and future scope

The results confirm that each modality contributes unique strengths, and their combination through multimodal learning significantly enhances diabetes prediction. While CNNs detect visual complications, FFNNs handle physiological data, and BERT understands historical context—only the fusion model effectively brings these together, offering clinicians a trustworthy and accurate AI tool for decision support.

Future Scope

The future of multimodal deep learning in diabetes diagnosis holds immense potential for both research and real-world application. One key direction involves gaining access to unified patient-level datasets that contain synchronized retinal images, lab results, and clinical notes, which would enhance the accuracy and clinical reliability of predictive models. Expanding the modalities to include genomic data, wearable sensor outputs, and longitudinal glucose monitoring can further strengthen early detection and personalized care. Additionally, deploying optimized models on mobile or edge devices could bring diabetes screening tools to underserved or rural populations, promoting real-time, accessible healthcare interventions.

Another crucial area of advancement lies in incorporating Explainable AI (XAI) to make predictions more transparent and clinically interpretable. Tools like SHAP, LIME, and Grad-CAM can help uncover the rationale behind AI decisions, fostering trust among healthcare providers. Future work can also focus on time-series modeling for predicting disease progression and exploring privacy-preserving techniques such as federated learning to enable secure, large-scale deployment across hospitals. Ultimately, this multimodal framework can evolve into a comprehensive diagnostic platform capable of detecting not only diabetes but also its complications and co-morbid conditions like cardiovascular disease, making it a powerful tool for integrated, AI-driven healthcare.

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