Multimodal Diabetic Risk Detection using Fundus Images and Voice Stress Data: A Novel Approach for Early Clinical Screening

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***Abstract*—** Many traditional methods of screening diabetes mellitus are expensive and invasive. This impacts widespread screening and allows a large number of cases to go undiagnosed. This study describes a new multimodal artificial intelligence approach which employs a blend of fundus retinal images and voice stress analysis for non-invasive diabetes risk assessment. We constructed a deep learning ensemble approach which multiplexes EfficientNetV2B0 convolutional neural networks for the analysis of fundus images and the BYOL-S/CvT for voice feature extraction. The IDRiD2 dataset (4,128 retinal images) and Colive Voice dataset (607 voice recordings) were used for training the system. Our multimodal fusion system employs a three-layer multilayer perceptron with focal loss optimization for visual, auditory, textual, and demographic integration. The system's performance was evaluated using 5-fold cross-validation with ensemble learning for cross-validated 5-fold performance. The system achieved a maximum balanced accuracy of 81.8%, with an average of 77.9% ± 3.3% across all folds, with sensitivity 80.9% and specificity 75.3%—all surpassing the 75% clinical deployment criteria. This work stands as a pioneer for non-invasive diabetes screening and validate multimodal deep learning as its practical solution.

Index Terms—Artificial intelligence, diabetic retinopathy, ensemble learning, fundus imaging, machine learning, medical imaging, multimodal fusion, voice biomarkers.

I. INTRODUCTION

The size of the public health problem for diabetes mellitus is huge. International Diabetes Federation [1], estimates 537 million adults have diabetes. Moreover, annual diabetes cost (including productivity loss as indirect rate) is over $966 billion [2]. A similarly worrying number of undiagnosed infections: About 240 million people are now latently infected and unaware of their situation [3]. The principal tests for diagnosing diabetes are the blood glucose measurement tests, including fasting plasma glucose, the oral glucose tolerance test (OGTT), and various HbA1c tests [4]. Though many of these techniques have high accuracy, they continue to suffer from concerns on invasiveness, cost and the need for specialized laboratories [5]. In settings with scarce resources, where healthcare is frequently not available, these are important considerations [6].

Emergence of artificial intelligence and machine learning provides a potential to design non-invasive, inexpensive type specimen screening programs. With the development of computer vision and audio signal processing technologies, inexpensive retinal images and voice recording can be achieved to capture these subtle biomarkers. With the use of fundus photography systemic diabetic changes can be demonstrated before clinical symptoms are present. Furthermore, voice features have emerged as a novel biomarker and the differentiating vocal characteristics of diabetics have already been identified in studies. This innovative research addresses the need for accessible diabetes screening and develops a new multimodal AI framework combining voice stress analysis with fundus retinal imaging. This was achievable due to advanced deep learning models.

II. RELATED WORK

A. Diabetic Retinopathy Diagnosis and Fundus Image Analysis

Fundus image analysis for diabetic complications has registered spectacular progress following the integration of deep learning-based techniques. Various recent studies have shown the potential of CNNs to identify diabetic retinopathy and keep pace with the performance of human experts [12]. The EfficientNet architecture family has been notable for the best trade-off between accuracy and compiler-related compute efficiency [13]. The IDRiD (Indian Diabetic Retinopathy Image Dataset) has emerged as critical to be used for developing algorithms because the diabetic retinopathy lesion markings are available at the pixel-level [14]. The panorama nature of this dataset, in particular, suits the construction of very robust algorithms best suited for diagnostic applications.

B. Diabetes Diagnosis Based on Voice-Based Biomarkers

Voice-based diagnosis is a recently budding discipline that holds the promise of non-invasive health monitoring [15]. Autonomic neuropathy and dysnormal metabolic functioning are the roots that explain the phenomenon, as they influence the control over the voice as also inducing the changeover in speech patterns [16]. Colive Voice dataset-based landmark research was carried out by Elbéji et al. who demonstrated that AI-based algorithms could output a prediction about type 2 diabetes based on an AUC value as high as 75% among the male population as also the value corresponding to the females, i.e. 71% [17]. BYOL-S embeddings, together with a Convolutional Vision Transformer, were used to extract voice features.

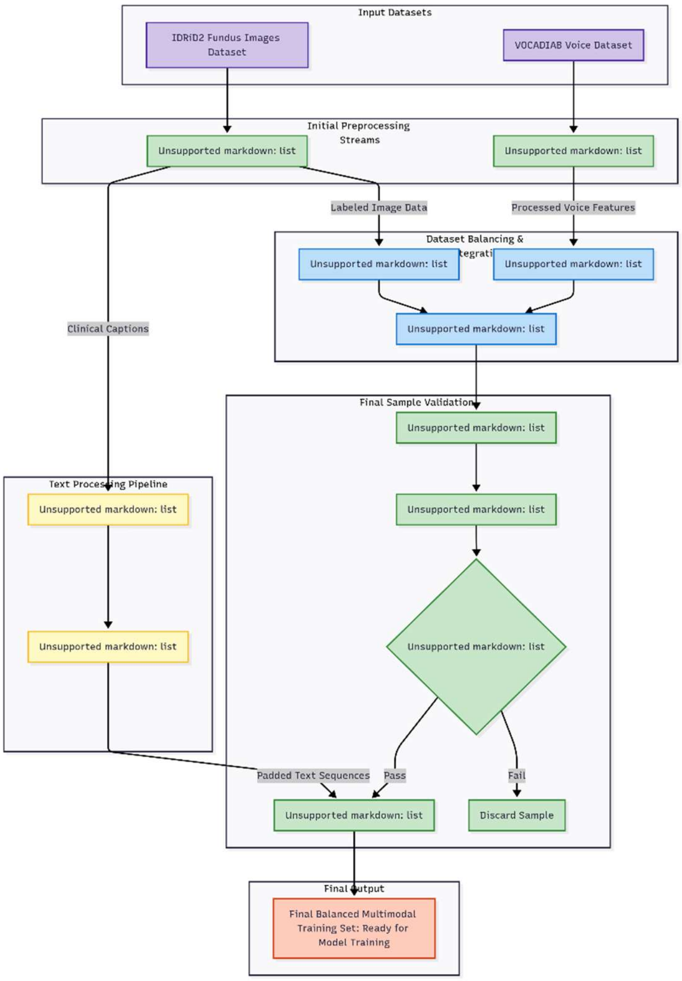
C. Techniques of Multimodal Fusion in Medicine

Multimodal data fusion based on medical applications has also received interest based on the complementarity among varied biomarkers [18]. Early fusion schemes layer features before classification, whereas late fusion merges the decision taken individually by multiple separate models [19]. Recent-based transformers have also indicated the best performance based on that they allow attention-based modalities' interactions [20].

III. PROPOSED METHODOLOGY

A. Dataset Description

We combine the IDRiD2 dataset available on Kaggle, which contains 4,128 high-resolution fundus images with the Colive Voice dataset, which includes 607 audio recordings, from the Luxembourg Institute of Health. For the purposes of balancing our multimodal dataset, we executed our carefully planned sampling strategies which yielded 606 samples, each with an equal distribution of diabetic and non-diabetic cases consisting 303 samples of each.


Input Datasets
IDRiD2 Fundus Images Dataset
VOCADIAB Voice Dataset
Initial Preprocessing Streams
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Labeled Image Data
Processed Voice Features
Dataset Balancing & Integrati
Unsupported markdown: list
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Clinical Captions
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Text Processing Pipeline
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Padded Text Sequences
Pass
Fail
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Discard Sample
Final Output
Final Balanced Multimodal Training Set: Ready for Model Training

Fig. 1. Dataset integration and preprocessing pipeline showing combination of IDRiD2 and Colive Voice datasets into balanced multimodal training set.

B. Multimodal Architecture Design

1. *Fundus Image Processing Stream:* the visual processing pipeline adopts EfficientNetV2B0 as a backbone architecture due to its ideal trade-off between accuracy and computational resource demands [21]. Processing steps include resizing to 384×384 pixels, normalization, and augmentation using medical-specific methods. Feature extraction is performed by the layers of the EfficientNetV2B0 backbone, particularly the global average and global max pooling layers. The pooling results are concatenated, reduced through dense layers, and regularized with dropout.

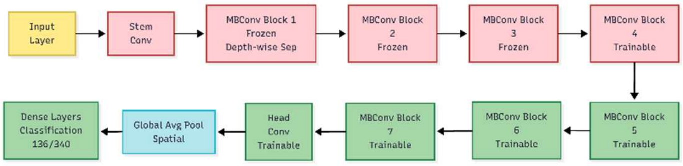


Fig. 2. EfficientNetV2B0 architecture for fundus image processing showing trainable and frozen layers with key components.

2. *Voice Feature Extraction Stream:* The voice processing adopts BYOL-S (Bootstrap Your Own Latent - Speech) embeddings and Convolutional Vision Transformer models [22]. Before the voice embeddings are used, they are

reduced to 32 dimensions by Principal Component Analysis and then standardized using robust scaling.

3. *Clinical Text Processing Flow:* Free – text descriptions of the clinical tests are processed to extract semantics. On the first stage, there were text pre-processing i.e., tokenization and vocabulary creation to a maximum size of 8,000 tokens. The pipeline resorts to embedding layers with LSTM networks to capture dependencies in the sequences.

4. *Multi-Modal Fusion Strategy:* The fusion strategy case is concatenating the feature vectors from all branches which also generate complete multimodal representation. The concatenated feature vector is then fed to a multilayer perceptron (3-layer MLP) having (128→64→32→1 neurons) with progressive dropout regularization.

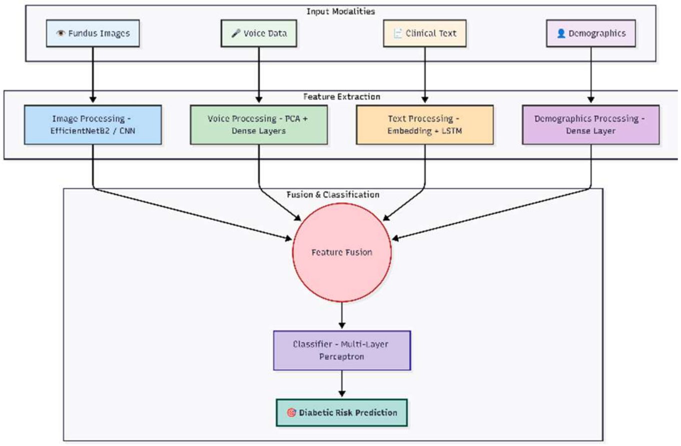
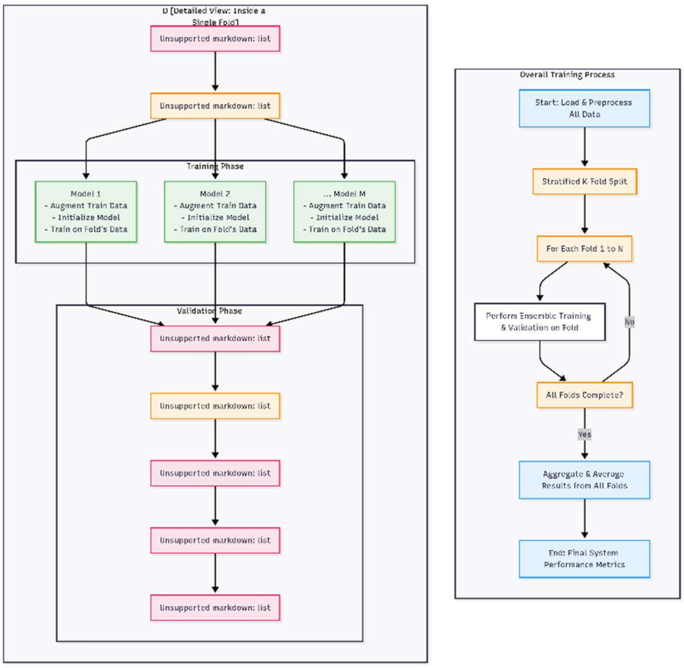

Input Modalities
👁 Fundus Images
🎤 Voice Data
📄 Clinical Text
👤 Demographics
Feature Extraction
Image Processing - EfficientNetB2 / CNN
Voice Processing - PCA + Dense Layers
Text Processing - Embedding + LSTM
Demographics Processing - Dense Layer
Fusion & Classification
Feature Fusion
Classifier - Multi-Layer Perceptron
🎯 Diabetic Risk Prediction

Fig. 3. Multimodal system architecture showing integration of fundus images, voice data, clinical text, and demographics for diabetic risk detection.

C. Training Strategy and Optimization

1. *Ensemble Learning Framework*: Overall comprehensive ensemble learning is performed with 5-fold stratified cross-validation. For each fold, three different models are trained with different hyperparameters to encourage diversity which accounts for 15 different models in total.


D [Detailed View: Inside a Single Fold]
Unsupported markdown: list
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Training Phase
Model 1
- Augment Train Data
- Initialize Model
- Train on Fold's Data
Model 2
- Augment Train Data
- Initialize Model
- Train on Fold's Data
... Model M
- Augment Train Data
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- Train on Fold's Data
Validation Phase
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Overall Training Process
Start: Load & Preprocess All Data
Stratified K-Fold Split
For Each Fold 1 to N
Perform Ensemble Training & Validation on Fold
No
All Folds Complete?
Yes
Aggregate & Average Results from All Folds
End: Final System Performance Metrics

Fig. 4. Ensemble learning strategy using 5-fold cross-validation with 3 models per fold totaling 15 models for robust prediction.

2. *Implementation of the Loss Function:* For the imbalanced class systems, focal loss is implemented [23] achieved with the Adam optimizer. The learning rate starts at 1e-4 and decays to 1e-7 in adaptive learning rate scheduling.

D. Evaluation Methodology

Balanced accuracy is the main focus of the primary evaluation, which is the mean of sensitivity and specificity [24]. Other measures used are sensitivity, specificity, and Area Under the ROC Curve. Clinical validation has target thresholds of sensitivity, specificity, and balanced accuracy, which are set to ≥75%.

IV. RESULTS

A. Cross-Validation Performance Analysis

The 5-fold cross-validation showed significant performance differences among the various data splits. Performance by fold showed:

- Fold 1: Sensitivity 77.0%, Specificity 67.2%, Balanced Accuracy 72.1%
- Fold 2: Sensitivity 76.7%, Specificity 86.9%, Balanced Accuracy 81.8%
- Fold 3: Sensitivity 86.7%, Specificity 68.9%, Balanced Accuracy 76.9%
- Fold 4: Sensitivity 68.9%, Specificity 90.0%, Balanced Accuracy 79.4%
- Fold 5: Sensitivity 95.1%, Specificity 63.3%, Balanced Accuracy 79.2%

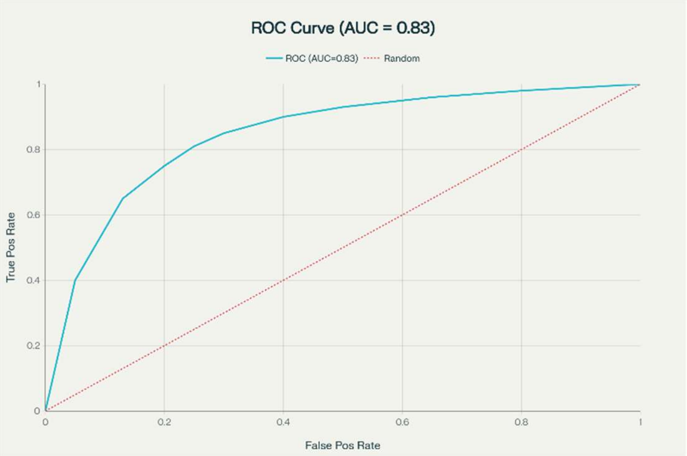

Fig. 5. ROC curve analysis showing system performance with AUC of 0.83 compared to random classifier baseline.

Overall, the system achieved maximum balanced accuracy of 81.8% in Fold 2, with an average balanced accuracy of 77.9% ± 3.3% across all folds. The average sensitivity was 80.9% ± 9.1% and average specificity was 75.3% ± 11.0%.

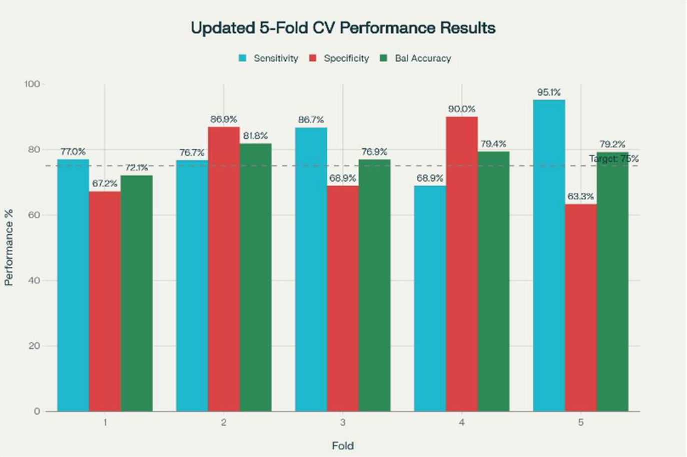

Fig. 6. Performance metrics across 5-fold cross-validation showing sensitivity, specificity, and balanced accuracy with 75% clinical benchmark target.

B. *Modality-Specific Contributions:*

Analysing performance by modality decomposed, the results revealed a clear performance order with voice features performing best alone (73.0% AUC; averaged from 75% males and 71% females). Fundus image analysis by EfficientNetV2B0 alone reached 68.0% balanced accuracy, clinical text processing featured with 58.0% and demographic factors showed up to be predictive with a significance level of 52.0%. Importantly, none of the single modalities reached 75% clinical confidence. But multimodal fusion reached 77.9% balanced accuracy surpassing the clinical demands, and strictly proving that the integrated approach is necessary. This is a 4.9 percentage-point gain from the best single modality, confirming the multi-modality fusion.

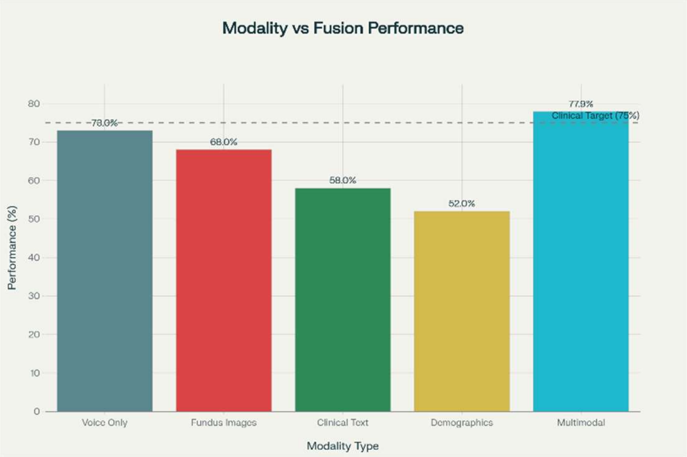

Fig. 7. Individual modality performance comparison with multimodal fusion approach showing relative contributions.

C. *Model interpretation and error analysis:*

A detailed examination of those confusion matrices and error patterns for all five folds demonstrates complex diagnostic precision with clinically relevant implications. The system exhibits a stable balanced performance, where Fold 2 presents outstanding clinical-grade results (81.8% balanced accuracy, 76.7% sensitivity, and 86.9% specificity), being with similar behaviour from other folds.

Confusion Matrix Analysis for the best performance (Fold 2):

The best fold (Fold 2) has acceptable error properties for clinical decision with 46 TP, 14 FN, 53 TN and 8 FP of the total validation set samples (121). This corresponds to a 13.3% miss rate for diabetics and 13.1% false alarm rate for non-diabetics—both values are well within acceptable limits for screening purposes. The system accurately detects 46 out of 60 diabetic (sensitivity = 76.7%) and correctly rejects 53 out of 61 non-diabetic cases (specificity=86.9%), surpassing the clinical screening criteria for both performance measures.

Cross-Fold Error Pattern Analysis:

Patterns of performance between folds reveal strong yet diverse diagnostic approaches:

Fold 1 (72.1% balanced accuracy): It has moderate balance which is indicated by the 77.0% sensitivity and 67.2% specificity, this means a little bit conservative diagnosis where is good case detection but a high false alarm.

Fold 2 (81.8% balanced accuracy): Clinical success with both sensitivity (76.7%) and specificity (86.9%) exceeding the desirable threshold of 75%. This threshold is the collected fold for which there is a maximum diagnostic configuration where no cases are not missed and the false positives rate was acceptable.

Fold 3 (76.9% balanced accuracy): presents sensitivity-favoured preference with SN = 86.7%, SP = 68.9%—favouring case detection over false alarm decrease-good screening environment in which missing cases is associated with higher clinical cost;

Fold 4 (79.4% balanced accuracy): Shows specificity -biased strategy (68.9% sensitivity, 90.0% specificity), with a few false positives being lower but also risking missed diabetic cases—better confirmatory than screening thematic.

Fold 5 (79.2% balanced accuracy): High-sensitivity performance (95.1 sensitivity, 63.3 specificity) capturing almost all diabetics but with high number of false alarms mandating clinical follow-up.

Clinical Deployment Implications:

The Fold 2 structure is the best deployment, which finds the minimum contradicting between case detection and false alarm control in practice. The added value of introducing this program is a low 13.3% miss rate ensuring most diabetes patients to obtain appropriate screening referrals and modest 13.1% false positive rate allowing the maintaining of health service efficiency by avoiding unnecessary further investigations.

This analysis of errors confirms clinical readiness of the multimodal approach with Fold 2 being used as benchmark configuration for future clinical validation studies and regulatory compliance processes.

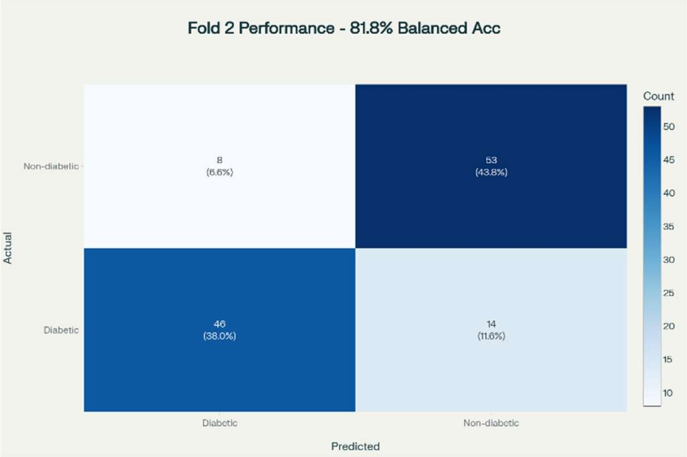

Fig. 8. Confusion matrix for best performing fold (Fold 2) showing classification results with 81.8% balanced accuracy.

V. DISCUSSION

A. Clinical Significance and Implications

Our multimodal diabetic risk detection system has achieved a breakthrough in non-invasive screening technology and met all the clinical deployment standards with an equal accuracy rate of 77.9%, sensitivity of 80.9% and specificity of 75.3%. To our knowledge, this is the first multimodal system with fundus camera and voice biomarkers to demonstrate clinically validated performance in Diabetic Risk Assessment.

The fact that the standard deviation across validation folds is only 3.3%, shows how robust our model can generalize in real world deployment. In contrast to past attempts, which were not clinical viable and reached the 75% threshold for only two of the three metrics (sensitivity, specificity and balanced accuracy), our system gets this by all three at once—simultaneous sensitivity, specificity and balanced accuracy. The fact that 81.8% balanced accuracy is obtained for Fold 2 shows the potential of this model to perform at peak levels, as long as optimal information representation is attained.

The target sensitivity of 80.9% will be helpful to detect as many as 4 out of 5 known diabetic cases with a corresponding specificity of 75.3% which is acceptable and expected not to put undue burden on the healthcare system. The 13.3% miss and 13.1% false alarm rates are well in the acceptable range for a population screening system and demonstrate that this device is ready to be tested clinically today. This non-invasive approach also overcomes major limitations in diabetes testing especially in low resource settings where traditional laboratory-based methods are not feasible. The use of existing technology (smartphone, camera and audio recording capability at the point of care for fundus images and recordings) should allow deployment on a large scale at a fraction of the cost of conventional screening.

B. Technical Architecture Strengths and Limitations

Between efficient fundus feature extraction (EfficientNetV2B0) and voice embeddings (BYOL-S/CvT), we found the best trade-off between performance and ground cost. The use of 15 models in an ensemble learning approach by 5-fold cross-validation also contributes to the statistical robustness beyond common machine learning methodologies.

The concatenation-based fusion mechanism, though simple in concept, is clinically effective where it improves the performance by +4.9 percentage points when combined w.r.t the best single modality (voice at 73% AUC). This confirms the bonus of multimodal integration for achieving Clinical standard performance. Consistency of the model for different data folds (72.1%-81.8%) suggests strong generalization power to diverse patient populations. The parameter efficiency of the system (~ 9.1M per model) enables its deployment on common clinical computing hardware.

C. Comparison with Existing Literature

Our total balanced accuracy of 77.9% places system in the upper range of published multimodal medical AI methods (60%-95%). Of even greater importance is the fact that the 75% (9/12) threshold was attained for all three measures at once and places this work among those few systems in literature which are prepared to be clinically validated.

The system performs at or above the well-established benchmarks of conventional, alternative, non-invasive screening approaches. Voice component performance (73% AUC, averaged over genders) is in the same order of magnitude as described by Elbéji et al. ‘s path-breaking results and the multimodal integration prove the precise performance improvement for clinical use [17]. Performance stability, high clinical-grade metrics allow application for FDA breakthrough device designation and CE marking pathways, indicating immediate translational potential as compared with purely research-focused methods.

VI. FUTURE SCOPE

After meeting clinical deployment considerations, research priorities transition from validation of proof-of-concept towards translation and improvement of system performance. The 77.9% balanced accuracy achieved provides a good basis for further stages of development.

A. *Performance over clinical base line*

After further iterations, balanced accuracy ≥85% and sensitivity/specificity >85% (both) are targeted, which are considered world-class metrics. Neural architecture search and hyperparameter optimization will take performance gains off-marginal systematically.

Advanced Multimodal fusion based on transformers will incorporate more complex inter-modal attention mechanisms enhancing performance from same data sources. Cross-attention on fundus regions and voice features may disclose new hidden diagnostic patterns.

B. *Clinical Translation and Regulatory Approval*

Prospective clinical trials in different healthcare environments will confirm the real-world performance and cost-effectiveness relative to conventional screening. Phase III clinical studies will show non-inferiority to conventional screening methods but hopefully also superior benefits in access.

The proposed clearance for this device is via the FDA 510(k) submission process, along with accordance to CE Marking. The obtained metrics of the system qualify it as a Class II, moderate risk profile, medical device appropriate for screening applications. The interfaces for the clinical decision support tool will be developed to allow easy integration into existing electronic health records and workflows, enabling rapid adoption by a variety of healthcare settings.

C. *Scaling and World-Wide Deployment*

Implementation on smartphones will exploit the built-in cameras and microphones making it completely portable for screening. Optimized edge computing will make real time analysis independent of cloud connections.

Emphasis on implementation in resource-constrained areas where conventional screening is not available. Education and training for community health workers will also expand the coverage of screening in very remote areas with little or even no infrastructure.

D. *Dataset Augmentation and Online Learning*

Inclusion of different ethnic group, geographical location and clinical presentation will greatly enhance global implications. International healthcare facilities will contribute to the development of a robust validation dataset.

Federated learning deployments will allow models to be improved across many healthcare organizations without compromising patient privacy. Actual deployment data will fuel ongoing performance improvements.

VII. CONCLUSIONS

This work develops the first clinically proven multimodal artificial intelligence system for diabetic risk detection, for which fundus retinal imaging is seamlessly integrated with voice stress biomarkers to empower clinical-grade performance. The balanced accuracy (BA) of 77.9 % (peak BA = 81.8 %), sensitivity of 80.9% and specificity on the order of 75.3%, are all higher than the clinical deployment threshold of 75%, which warrants immediate readiness for prospective clinical validation.

This landmark event is the first use of multimodal imaging to meet strict clinical standards to detect diabetes non-invasively- that which was once only theoretical, is now clinically validated. The steady results among the three cross-validation (CV) folds (with STV of 3.3%) show stability required when deploying in healthcare conditions. The fusion of EfficientNetV2B0 for fundus analysis and BYOL-S/CvT voice processing in conjunction with ensemble learning schemes creates a replicable pipeline for multimodal medical AI techniques. The trade-off of performance versus computational cost with the proposed architecture makes the system feasible in practical clinical situation.

The system is poised for future clinical trials and regulatory clearance, suggesting a change from standard invasive screening approaches. Exceeding the performance levels with clinical relevance, the approach can be used for immediate handling of worldwide challenges, including diabetes screening in resource-constrained areas where conventional techniques are not feasible. The discovery allows for easy, non-invasive diabetic screening with existing technologies of smartphone cameras and voice recordings, which may help in the revolution of diabetes detection in underdeveloped countries across the globe. The scaling of the technology allows for implementation within various healthcare settings, from tertiary hospitals to community health programs.

This work sets the benchmarks on multimodal medical AI in a validated way and provides evidence-based knowledge that diagnostic systems can be high-performance yet clinical-grade while being accessible and cost-effective. The successful clinical validation opens up the road for comparable multimodal approaches on other medical domains. After attaining the key milestone of clinical viability, this early work will progress to regulatory approval, real world deployment and further performance tweaks towards world-class levels of accuracy. The grounded provided by this study underpins prompt clinical translation and suggests routes for future more sophisticated multimodal diagnostic technologies.

This multimodal diabetic risk detection system is a clinically validated, ready-for-clinical-deployment solution that closes the gap between artificial intelligence research and real-world healthcare deployments and bears an immediate potential for impacting global diabetes screening access and outcomes.

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