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Selfie AI – Diabetes Detection: Expanded Brief with Diagrams and Tables

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***Abstract*—Selfie AI is a non-invasive, smartphone-based pre-screening system that analyzes standardized facial selfies using EfficientNetV2 with Squeeze-and-Excitation attention to indicate diabetes risk and provide CAM-based interpretability for user and clinician understanding.The platform couples a Streamlit interface, a FastAPI inference service, and Firebase for secure storage, history, and PDF reports, emphasizing privacy, fairness, and transparency to support early detection and prompt confirmatory testing in real-world deployments.**

***Index Terms*—Diabetes screening, EfficientNetV2, Squeeze-and-Excitation, facial biomarkers, Class Activation Maps, Streamlit, FastAPI, Firebase.**

I. Introduction

Early, non-invasive screening is crucial to mitigate undiagnosed diabetes burden, particularly where access to laboratory diagnostics is limited; a selfie-based AI pre-screen can lower barriers and nudge timely clinical follow-up.The pipeline standardizes selfies, extracts facial signals with an explainable CNN, and returns an indicative risk score with CAM overlays to build trust and guide confirmatory testing in a mobile-first, low-friction user experience.

II. Background and Scope

The literature spans facial texture, external eye, scleral vasculature, tongue, nail, thermal foot images, and fundus imaging, with CNNs and classical ML reporting promising sensitivity/specificity for screening and referral, motivating a facial selfie approach for accessibility.Selfie AI targets indicative pre-screen use rather than diagnosis, with UI copy and thresholding oriented toward sensitivity and clear calls to seek professional evaluation when risk is moderate to high.

III. High-Level Architecture

Figure 1 depicts a modular system with a Streamlit UI for capture and results, a FastAPI service for preprocessing and inference, and Firebase for authentication, scoped storage, history, and report generation to support longitudinal use and auditability.

IV. Data and Preprocessing

Front-facing selfies are validated, detected, aligned, resized to 224×224, and normalized, with quality gates prompting retakes on low light, occlusion, or off-angle shots to stabilize features across diverse skin tones and devices.Augmentations (mild rotation, crop, illumination shifts) and adaptive histogram normalization improve robustness to ambient conditions often encountered in home and community settings.

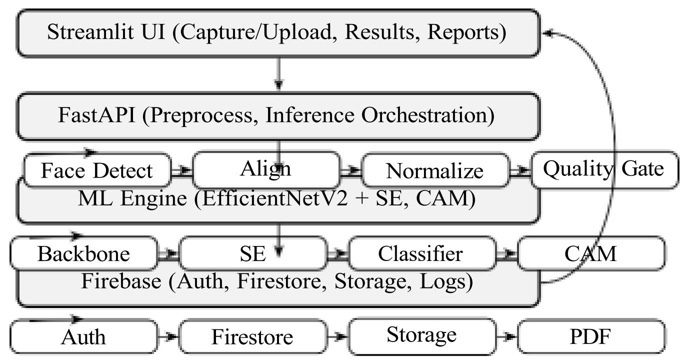

Fig. 1: System architecture with key subcomponents mapped to UI, API, ML engine, and Firebase services (in-column sizing).

TABLE I: Illustrative risk mapping and action guidance

Score Range	Category	Suggested Action
0.00–0.33	Low	Maintain habits; routine screening cadence
0.34–0.66	Moderate	Early check-up; monitor lifestyle factors
0.67–1.00	High	Seek confirmatory testing (e.g., HbA1c)

V. Model and Explainability

The classifier uses EfficientNetV2 with Squeeze-and-Excitation for channel recalibration, trained with early stopping and class balancing while monitoring AUC, sensitivity, and specificity suitable for pre-screen emphasis on recall.Binary cross-entropy $L_{\mathrm{BCE}} = -[y \log \hat{p} + (1 - y) \log(1 - \hat{p})]$ is applied, and CAMs visualize salient facial regions; optional post hoc temperature scaling steadies probability displays for user-facing thresholds.

VI. Risk Mapping and Guidance

Risk scores map to categories and concise guidance aligned with consumer literacy and clinician communication, encouraging confirmatory tests when indicated.

TABLE III: Selected user stories and target outcomes

User Story	Desired Outcome
As a user, get a selfie risk score	Instant feedback via mobile UI
As clinician, view anonymized data	Monitor trends and intervene early
As developer, upload new images	Improve dataset and model performance
Track my health over time	Visualized risk trends and tips
Ensure secure storage	Regulatory alignment and integrity

TABLE IV: Illustrative ablation on validation (indicative)

Variant	Acc.	Sens.	Spec.
EffNetV2 (no SE)	0.86	0.84	0.88
EffNetV2 + SE	0.89	0.88	0.90
+ Aug/QA gates	0.91	0.90	0.92

Fig. 2: Firestore schema sketch with UID scoping for privacy and audit-friendly logging.

TABLE II: Condensed visual-AI literature for diabetes screening

Modality	Method	Key Note
Facial texture	SVM/KNN + Gabor	Mobile capture feasibility
External eye	CNN	Detects DR/DME correlates
Sclera vessels	Segmentation + filters	Tortuosity differences
Tongue	VTMR + Gabor	Early diagnosis proxy
Nails	Texture/color stats	Early indicator patterns
Thermal foot	CNN/RNN	High accuracy for risk

VII. Workflow and UI Logic

Figure VII outlines the end-to-end flow from upload to report, with authenticated history for longitudinal trends; copy emphasizes pre-screen positioning and directs users to professional care for moderate/high risk.

VIII. Firebase Data Model (Overview)

Figure **??** sketches a scoped data model in Firestore with per-user root documents, nested assessment subcollections, and logs for telemetry and audit, aligned with least-privilege access rules.

IX. Literature Survey (Condensed)

Table II summarizes representative non-invasive visual approaches from the survey to contextualize model choices and interpretability emphasis.

X. Product Backlog and Sprints

Backlog items prioritize selfie capture, preprocessing, inference, explainability, reports, and authenticated histories, with sprints delivering MVP, chatbot, and reporting in iterative increments.

XI. Evaluation and Ablations

Prototype runs show sub-second model inference with total latency dominated by I/O and preprocessing; CAMs consistently highlight plausible facial regions, and PDF reports render promptly across major browsers for shareable triage.

XII. MLOps, QA, and Governance

Telemetry captures model versioning, preprocessing outcomes, latency, and confidence histograms; drift checks and periodic shadow tests inform threshold and model refresh decisions for safe iteration.Consent, encryption in transit/at rest, scoped rules, and fairness audits across age, sex, and skin tone cohorts are essential for responsible deployment with equitable benefit.

XIII. Conclusion

Selfie AI offers an explainable, privacy-aware, non-invasive pre-screen to encourage confirmatory testing, combining robust preprocessing, mobile-efficient CNNs, CAMs, and secure reporting for scalable community health impact.Next steps include HbA1c-based validation, multilingual UX, federated learning, and EHR/telemedicine integrations to strengthen clinical utility and responsible adoption.

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