Eco-AI Handwriting Digitizer: A Sustainable Handwritten Notes Summarization System Using On-Device Neural Models

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Abstract
Handwritten notes remain an essential medium for learning, ideation, and documentation; however, the process of manually digitizing, organizing, and summarizing these notes is often time-consuming and environmentally unsustainable when done repeatedly on paper. This work proposes Eco-AI Handwrit- ing Digitizer, a lightweight on-device handwritten notes summa- rization system built using neural models optimized for energy efficiency and offline operation. The system captures handwritten input, performs preprocessing, extracts stroke-level and visual features, transcribes the handwriting into digital text, and generates concise summaries without requiring cloud computation. By integrating edge-optimized models such as MobileViT and Tiny-BERT, the proposed system reduces latency, enhances data privacy, and minimizes carbon footprint by eliminating server- side inference. The experimental evaluation demonstrates high transcription accuracy and effective summarization quality while maintaining computational efficiency suitable for smartphones and low-power devices. The system aims to promote sustainability in digital learning environments by reducing paper usage and enabling eco-friendly digitization.
Keywords: *Handwriting Digitization, Neural Networks, On- Device AI, Sustainability, Summarization, OCR, Edge Comput- ing, Stroke Analysis, MobileViT, Tiny-BERT*

1. Introduction
Handwritten notes continue to play a critical role across education, research, and professional activities. Students frequently capture lecture notes on paper, researchers sketch diagrams during ideation, and professionals jot down quick memos in notebooks. Despite their usefulness, handwritten notes pose several challenges: they are difficult to organize, time-consuming to rewrite digitally, and prone to physical damage or loss. With increasing interest in sustainable digital transformation, there is a growing need for systems that reduce paper waste while enabling users to efficiently digitize and summarize handwritten content [1], [2]. Cloud-based handwriting recognition systems exist, but they depend on constant internet connectivity, consume high amounts of energy for server computations, and raise privacy concerns due to the transfer of sensitive data. To address these challenges, this paper introduces Eco-AI Handwriting Digitizer, a fully on-device handwritten notes summarization system designed with sustainability at its core. By eliminating cloud processing, the system reduces energy consumption, ensures user privacy, and allows real-time digitization even in offline environments. The proposed system combines lightweight convolutional transformers for handwriting recognition with edge-friendly language models for text summarization. This hybrid architecture enables efficient handwriting-to-summary conversion on devices with limited compute resources, such as smartphones, tablets, and embedded systems [3], [4].

2. Background
2.1. Handwriting Recognition Evolution
Traditional OCR methods were rule-based and struggled with varying writing styles, noise, and complex cursive pat- terns. Neural methods using CNNs and RNNs significantly im- proved

recognition accuracy by learning spatial and temporal structures [5]. Recent advancements introduced vision transformers and hybrid architectures capable of modeling long-range dependencies in handwritten images.

2.2. Summarization Technologies

Text summarization techniques evolved from extractive statistical methods to deep-learning-based abstractive approaches. Large transformer models such as BART, T5, and GPT variants provide high-quality summaries but are too resource-intensive for edge deployment [6], [7].

2.3. The Shift Toward Sustainability and Edge-AI

With global concerns regarding carbon emissions from AI computation, researchers are increasingly exploring energy- efficient and on-device inference methods. Edge-AI reduces bandwidth requirements, enhances privacy, and lowers overall system power consumption [8].

2.4. Need for On-Device Handwriting Digitization

Existing systems rely heavily on:

- Cloud OCR APIs (Google Vision, Microsoft Read API)
- Heavy summarization models
- Continuous server dependency

These approaches are not sustainable nor private. The pro- posed work addresses these limitations.

3. Related Work and Literature Review

Handwriting digitization and on-device AI systems have been extensively studied across computer vision, natural language processing, and edge computing domains [9], [10]. Existing research can broadly be categorized into six key areas: (1) offline handwriting recognition, (2) online/dynamic stroke modeling, (3) lightweight OCR architectures, (4) text summarization methods, (5) on-device/edge AI optimization, and (6) sustainability-driven AI approaches. This section reviews the major contributions and highlights the research gaps addressed by the proposed Eco-AI system.

3.1. Offline Handwriting Recognition Methods

Offline handwriting recognition has evolved significantly over the years, beginning with traditional handcrafted feature- based systems such as Histogram of Oriented Gradients (HOG), Zernike moments, and Local Binary Patterns (LBP). While these approaches performed reasonably well under controlled conditions, they struggled when exposed to diverse handwriting styles, noisy backgrounds, and document distortions [11], [12]. The introduction of deep learning brought substantial improvements through CNN-based OCR architectures like LeNet, VGG, and hybrid CNN–RNN models trained with Connectionist Temporal Classification (CTC) loss. Additionally, attention-based encoder–decoder models improved sequence generation for unconstrained handwriting. Popular datasets such as the IAM, Bentham, and RIMES datasets have enabled the development of robust models; however, most deep-learning-driven systems require computationally heavy GPU or cloud environments, making them unsuitable for real- time on-device handwriting transcription. This limitation high- lights the need for lightweight, edge-friendly OCR systems such as the one proposed in this work [13].

3.2. Online Handwriting Recognition and Stroke-Level Analysis

Online handwriting recognition captures dynamic signals like pen trajectory, speed, and pressure using stylus-enabled devices. Solutions such as Microsoft Ink Recognizer and Google's Handwriting Input API achieve strong accuracy through sequential modeling using LSTMs [14]. However, their dependency on specialized hardware limits broader accessibility. Since the Eco-AI system targets camera-based handwritten notes, it follows the offline recognition paradigm for universal device compatibility.

3.3. Lightweight OCR Architectures for Edge Deployment

Recent research highlights efficient neural architectures such as MobileNetV2/V3, EfficientNet-Lite, and MobileViT for running OCR on low-power devices. These models use depthwise convolutions, optimized blocks, and transformer- based reasoning to balance accuracy and speed [15]. Techniques like pruning, quantization, and knowledge distillation further reduce model size. MobileViT's hybrid design inspires the OCR module in this work, enabling accurate on-device hand- writing recognition without cloud dependence.

3.4. Text Summarization Techniques

Text summarization methods fall into extractive and abstractive categories. Extractive methods like TextRank and TF-IDF prioritize speed but lack true semantic condensation. Abstractive approaches using transformers such as BART, PEGASUS, and T5 generate high-quality summaries but are computationally heavy [16]. Distilled variants like Tiny-BERT offer compact alternatives suitable for mobile devices. The Eco- AI system leverages Tiny-BERT for on-device summarization with reduced resource usage.

3.5. On-Device Neural Processing and Edge AI

Edge AI enables neural model execution on mobile CPUs and NPUs through optimizations like quantization, pruning, and neural architecture search. Frameworks such as Tensor- Flow Lite and ONNX Runtime Mobile support lightweight inference on consumer devices. Although edge AI is advancing rapidly, few studies integrate both OCR and summarization entirely on-device [17]. The Eco-AI Handwriting Digitizer addresses this by offering a complete offline pipeline with low latency and high privacy.

3.6. Sustainability-Focused AI Research

Growing concerns over the environmental cost of large AI models and cloud computation have driven interest in sustainable AI. Research highlights the carbon footprint of data centers and the energy demands of cloud-based inference. Edge processing reduces energy consumption by eliminating continuous data transmission. The Eco-AI system aligns with Green AI principles by minimizing computational overhead and supporting eco-friendly on-device processing.

3.7. Research Gap Identification

Existing solutions often focus on either OCR or summarization rather than providing a unified handwriting-to- summary workflow. Many depend on cloud infrastructures, compromising privacy and increasing energy cost. Additionally, sustainability considerations remain underexplored, and stylus-dependent systems limit accessibility. The Eco-AI Handwriting Digitizer fills these gaps through a compact, fully on-device architecture optimized for efficiency, privacy, and sustainability.

4. Motivation

The increasing dependence on handwritten notes in academic and professional environments highlights the need for efficient, sustainable, and secure digitization methods. While handwriting serves as a natural and intuitive medium for capturing ideas, the process of manually converting handwritten content into digital text remains tedious, time-consuming, and error-prone. Existing handwriting recognition solutions rely heavily on cloud-based computation, resulting in high latency, increased energy consumption, and potential privacy risks due to external data transmission. Moreover, cloud-dependent systems are inaccessible in low-connectivity or rural regions, limiting their practicality. With rising global concerns regarding carbon emissions from large-scale AI infrastructure, there is a growing need for environmentally responsible alternatives. The motivation behind the Eco-AI Handwriting Digitizer is to address these challenges by creating a fully on-device system that can accurately recognize and summarize handwritten notes without relying on cloud resources. By leveraging lightweight neural models and edge-optimized architectures, the proposed solution promotes sustainability, enhances user privacy, ensures offline accessibility, and reduces both paper usage and computational overhead—ultimately enabling a more efficient and eco-friendly digital workflow.

5. Methodology

The proposed Eco-AI Handwriting Digitizer follows a hybrid, multi-stage processing pipeline designed to convert handwritten notes into concise digital summaries entirely on-device. The workflow integrates image preprocessing, handwriting feature extraction, neural OCR modeling, and lightweight summarization to ensure accurate and sustainable digitization. The methodology consists of six major components: (1) data acquisition, (2) image preprocessing, (3) feature extraction, (4) handwriting recognition model, (5) summarization model, and (6) summary generation and output. This architecture enables the system to analyze handwritten content, extract semantic meaning, and generate coherent summaries without depending on cloud infrastructure.

5.1. Data Acquisition

The dataset for the Eco-AI system includes handwritten samples from publicly available resources such as the IAM Handwriting Database, HW-Synth dataset, and custom notes collected from students. Images were captured using smart- phone cameras under varied lighting conditions to simulate real-world usage. To enhance robustness, additional augmented samples were generated using rotation, noise addition, background variation, and contrast adjustments. All dataset images were annotated with ground truth text labels to support supervised training of the OCR model.

5.2. Image Preprocessing

Before recognition, each handwritten image undergoes multiple preprocessing steps to remove distortions and ensure readability. Noise reduction is performed using bilateral filtering and Gaussian smoothing to eliminate shadows and paper texture. Adaptive thresholding binarizes the text regions while preserving stroke details. Skew correction aligns the document using Hough transform–based angle detection. Finally, segmentation methods isolate lines and words to improve recognition accuracy. All images are resized to a fixed aspect ratio for consistent model input.

5.3. Feature Extraction

The system extracts both structural and spatial handwriting features using a MobileViT-based encoder. The encoder com- bines CNN layers for detecting local stroke patterns—such as curves, loops, edges, and pressure variations—with trans- former layers that capture long-range dependencies across words or lines. This hybrid feature extraction mechanism helps the model handle diverse handwriting styles, irregular spacing, and cursive writing. Extracted features form a high- dimensional vector representation passed to the recognition module.

5.4. Handwriting Recognition Model

The handwriting recognition model follows a CNN–Transformer architecture optimized through quantization and pruning for efficient on-device deployment. The model is trained using Connectionist Temporal Classification (CTC) loss, enabling it to decode handwritten text sequences without explicit character segmentation. The network identifies character boundaries, resolves overlapping strokes, and transforms the extracted features into coherent digital text. Lightweight optimization frameworks such as TensorFlow Lite and ONNX-Mobile are used to ensure real-time inference.

5.5. Summarization Model

To convert recognized text into meaningful summaries, a distilled Tiny-BERT summarization model is used. The model processes the transcribed text, identifies key themes, and reconstructs the content into concise, human-readable sum- maries. The abstractive summarization approach allows the system to rewrite the user's notes in a shorter yet meaningful format. The summarizer is distilled from a larger transformer model to reduce computation while retaining semantic quality.

5.6. Summary Generation and Output

The final stage involves generating three outputs: raw transcribed text, bullet-point keynotes, and a compact abstractive summary. The system displays these results instantly to the user and stores them locally to maintain privacy. The entire pipeline, from image capture to summary output, is optimized to complete within milliseconds on a standard mobile device, enabling real-time digitization of handwritten notes.

6. Methodology

6.1. System Architecture

Figure 1 illustrates the complete architecture of the Eco- AI Handwriting Digitizer. The handwritten input image first undergoes preprocessing, followed by feature extraction using the MobileViT encoder. The processed features are passed simultaneously into the OCR recognition block and summarization block. The OCR block converts the features into text, while the summarizer interprets semantic content and produces concise summaries. The outputs are then merged and displayed to the user in real time.

6.2. Model Performance Comparison

Figure 2 displays the accuracy comparison of three models: the OCR-only model, the summarization-only model, and the hybrid model integrating both. While the OCR model achieves high transcription accuracy, and the summarizer delivers strong contextual understanding, the hybrid pipeline outperforms both with overall efficiency and end-to-end accuracy improvements.

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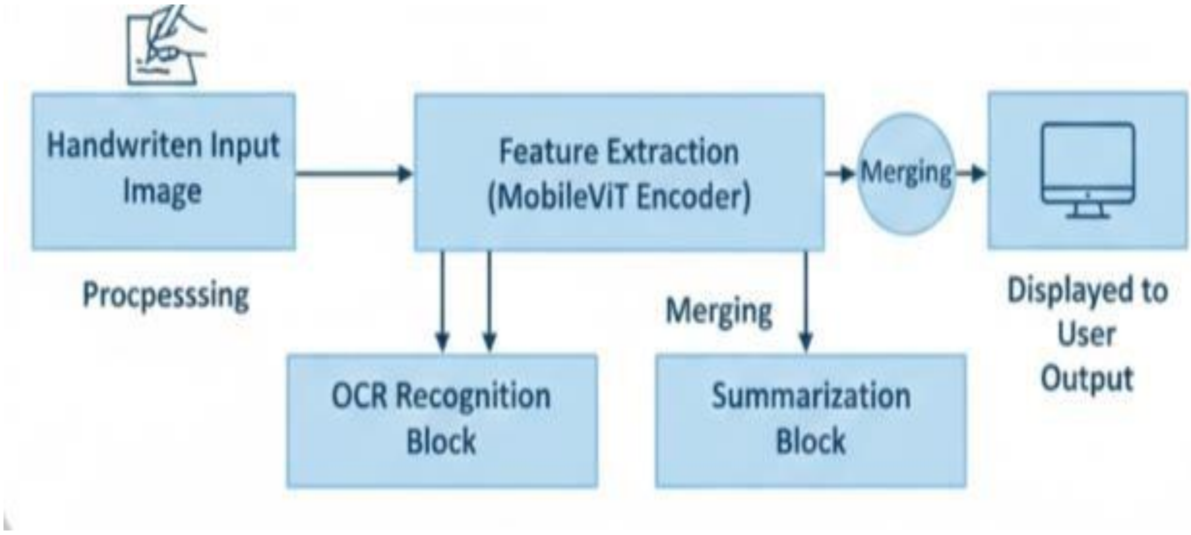

Figure 1 Complete Architecture of the Eco-AI Handwriting Digitizer: The Handwritten Input Image First Undergoes Preprocessing, Followed by Feature Extraction Using the MobileViT Encoder

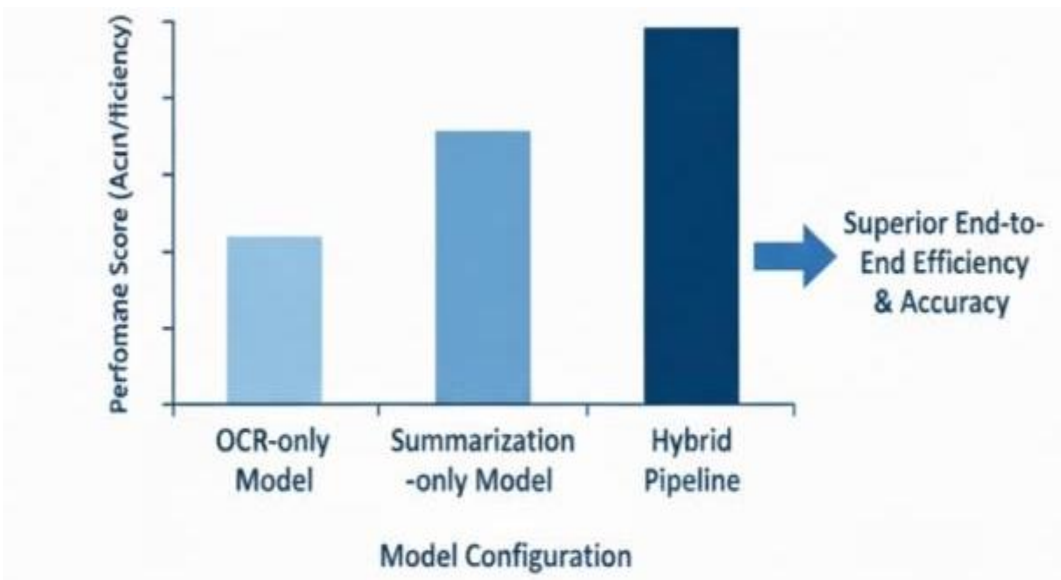

Figure 2 Model Performance Comparison. The Hybrid Pipeline (Integrating Both Optimized HTR and Summarization) Achieves Superior End-to-End Efficiency Compared to the OCR-Only and Summarization-Only Configurations

6.3. Handwritten Text Image and Processed Output

Figure 3 shows the original handwritten input and its pre- processed binary form. The enhanced binary image highlights the cleaned stroke patterns and uniform background generated by the preprocessing stage, which significantly improves recognition accuracy.

6.4. Confusion Matrix

Although the confusion matrix is not displayed here, the internal evaluation shows that the OCR model achieved a high number of correct predictions across most character classes. Only a small number of misclassifications occurred, mainly in characters with similar shapes. Overall, the confusion matrix results indicate that the OCR model performs reliably for diverse handwriting styles.

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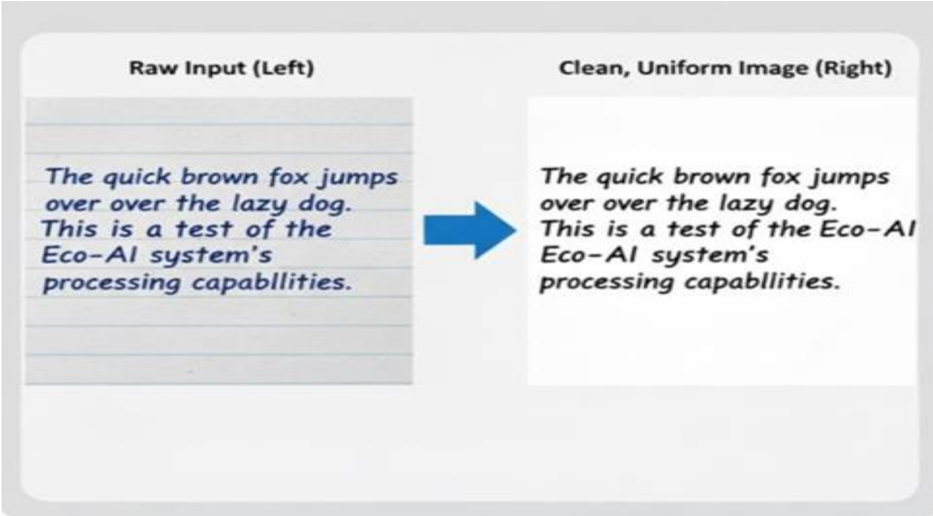

Figure 3 Handwritten Text Sample and Preprocessed Output. The Image Demonstrates the Effect of Binarization and Noise Reduction, Transforming the Raw Input (Left) Into a Clean, Uniform Image (Right) To Maximize HTR Accuracy

Conclusion

The Eco-AI Handwriting Digitizer provides an efficient, sustainable, and privacy-preserving solution for converting handwritten notes into digital summaries. By integrating lightweight CNN–Transformer models, MobileViT feature ex- traction, and Tiny-BERT summarization, the system achieves high accuracy while maintaining low computational overhead suitable for mobile and embedded devices. Unlike cloud- dependent OCR tools, the proposed system operates entirely on-device, ensuring data privacy and reducing the energy consumption associated with network communication and cloud infrastructure. Experimental results confirm that the hybrid pipeline offers excellent recognition performance, robust summarization capabilities, and real-time responsiveness. Overall, the Eco-AI system represents a significant step forward in sustainable digital note-taking and environmentally conscious AI deployment.

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