iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** V **Month of publication:** May 2025

DOI: https://doi.org/10.22214/ijraset.2025.71250

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

A Comparative Review of Lightweight Machine Learning Approaches for Handwriting-Based Dyslexia Detection

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Abstract: Dyslexia, a neurodevelopmental disorder affecting reading and writing skills, requires early detection to mitigate long-term educational impacts. Traditional diagnostic methods are time-consuming and subjective, prompting the adoption of automated handwriting analysis. This paper reviews lightweight machine learning (ML) approaches for dyslexia detection through handwriting, emphasizing computational efficiency, real-time applicability, and cross-linguistic adaptability. By evaluating techniques such as MobileNetV2, SSD Lite, Support Vector Machines (SVM), and Random Forests across languages like English, Hindi, Arabic, and Chinese, we highlight trade-offs between accuracy, efficiency, and script-specific challenges. Our analysis reveals that lightweight models achieve competitive performance while addressing issues like accessibility, making them valuable for use in resource-constrained environments like classrooms.
Index Terms: Dyslexia detection, Handwriting analysis, Lightweight machine learning, MobileNetV2, Multilingual screening, Explainable AI.

I. INTRODUCTION

Dyslexia, a neurodevelopmental disorder affecting 10–15% of individuals globally, impairs reading fluency, writing accuracy, and phonological processing. Traditional diagnostic methods—such as standardized literacy tests—are timeconsuming, subjective, and often inaccessible in low-resource educational settings. Early detection is critical to mitigate longterm academic and psychosocial impacts, yet manual screening remains impractical for large populations. This gap has spurred interest in automated, scalable solutions, particularly those leveraging handwriting analysis, which captures dyslexic markers like letter reversals, inconsistent spacing, and irregular stroke patterns.

Recent advancements in artificial intelligence (AI) have enabled handwriting-based dyslexia detection using machine learning (ML). Deep learning models, such as CNNs, achieve high accuracy but face challenges in computational complexity, data dependency, and cross-linguistic adaptability. Lightweight ML approaches—including MobileNetV2, SVM, and Random Forests—address these limitations by balancing efficiency and performance. These models are particularly suited for real-time use on edge devices (e.g., tablets or smartphones), making them very useful and viable for classroom use. However, their effectiveness varies across orthographies; for instance, Hindi's complex diacritics and Arabic's cursive script demand script-specific feature engineering, while English benefits from deep learning-driven visual pattern recognition.

This paper reviews lightweight ML techniques for dyslexia detection, comparing their efficacy across languages like English, Hindi, Arabic, and Chinese. We evaluate trade-offs between accuracy, computational cost, and adaptability, emphasizing practical applicability in multilingual contexts. By synthesizing insights from key studies, we aim to guide educators and developers in selecting context-appropriate models and highlight future directions for scalable, explainable, and linguistically inclusive screening tools.

II. RELATED STUDY

A. Handwriting-Based Dyslexia Detection

Handwriting irregularities are strongly correlated with dyslexia, serving as non-invasive biomarkers for early screening. Key studies highlight the role of machine learning (ML) in analyzing features such as inconsistent letter formation, spacing errors, and stroke distortions. It is a non-invasive method for identifying dyslexia, leveraging irregularities such as inconsistent letter formation, spacing errors, and stroke distortions. While traditional approaches relied on manual feature extraction, AI-driven techniques automate this process, enabling scalable screening. Challenges include script-specific complexities (e.g., diacritics in Hindi, ligatures in Arabic) and the need for robust multilingual datasets.

B. Dyslexia Across Languages

Dyslexia manifests differently across orthographies, necessitating script-specific adaptations:

- English: Deep orthography amplifies phoneme-grapheme mapping errors. Alkhurayyif & Sait (2023) used MobileNetV2[1] and SSD Lite [2] to detect letter-level anomalies, achieving 99.2% accuracy.
- Hindi: The abugida script introduces challenges like vowel diacritic (matra) misplacements and conjunct consonant errors. Venkatesh et al. (2021) designed an SVMCNN [9] hybrid for Hindi, prioritizing feature engineering (e.g., syllable-level errors) over deep learning, yielding 89% accuracy.
- Chinese and Arabic: Tan et al. (2022) adapted strokebased CNNs [10] for Chinese logographs [11] (78% accuracy), while Rodriguez & Kim (2024) addressed Arabic's cursive ligatures using ligature-aware CNNs (82% accuracy).

C. Deep Learning and AI for Dyslexia Detection

- CNN Architectures: Smith et al. (2020) used CNNs for English handwriting, achieving 99.2% accuracy by detecting spatial irregularities [13].
- Hybrid Models: Patel & Gupta (2023) combined CNNs with RNNs to analyze temporal handwriting patterns (97.6% precision) [14].
- Explainable AI (XAI): Ahmed et al. (2024) integrated Grad-CAM with CNNs to visualize dyslexic markers
- (e.g., reversed letters), enhancing interpretability [12].
- Transfer Learning: Mishra et al. (2024) fine-tuned pretrained CNNs for Hindi, reducing data dependency but achieving lower accuracy (85%) than hybrid models [15].

D. Challenges in Multilingual Dyslexia Detection

Despite advancements, dyslexia detection across multiple languages faces several challenges:

- Lack of multilingual datasets – Most studies are based on English handwriting data [5].
- Script complexity – Languages like Hindi, Arabic, and Chinese require specialized models for handwriting feature extraction [6] [7].
- Explainability of AI models – Studies such as Explainable AI in Handwriting Detection for Dyslexia [12] emphasize the need for transparent AI models.

III. METHODOLOGY

A. Dataset Overview

This study uses several benchmark datasets covering multiple languages:

- English – Dyslexia Dataset for Children
- Hindi – A custom dataset sourced from school board materials
- Arabic – The KHATT database, with specific annotations for dyslexia-related patterns
- Chinese – The CASIA-HWDB dataset, which contains handwritten character samples

B. Metrics for Evaluation

To evaluate and compare model performance fairly, several key metrics were used:

- Accuracy
- F1-score
- Precision
- Recall
- Interpretability
- Inference speed

C. Lightweight ML Models

1) MobileNetV2

MobileNetV2 is designed to be efficient by using depthwise separable convolutions, which lower computation by over 70% compared to traditional CNNs. It achieved strong accuracy across all language datasets, showing good adaptability with minimal adjustments.

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2) SSD Lite

SSD Lite, originally developed for object detection on mobile platforms, was used here to identify abnormalities at the letter level. It offers fast, real-time analysis but needs more memory to perform well.

Support Vector Machines (SVM) Support Vector Machines (SVMs), when used with features extracted from CNNs, performed well on smaller datasets. Their use of margin-based classification helps manage imbalanced data effectively.

3) Random Forest

Random Forest models combine multiple decision trees to improve accuracy and reduce overfitting. Although they are slower in inference, they remain easy to interpret and generally reliable.

4) Cross-Linguistic Evaluation

The models were tested across different writing systems. For English and Hindi, characters were processed individually. However, Arabic's connected script and Chinese's complex logographs required deeper feature learning and attention-based methods to capture patterns effectively.

D. Model analysis

This section explains the main machine learning models analyzed in this study and also includes their fundamental mathematical formulations. These equations help in understanding and clarifying the models' efficiency and applicability to handwriting-based dyslexia detection.

1) *MobileNetV2: Depthwise Separable Convolutions:* MobileNetV2 is primarily used in mobile vision applications and that also includes handwriting recognition.

It significantly reduces computation by factorizing standard convolutions into two operations:

- Depthwise convolution: Applies a single spatial convolution per input channel.
- Pointwise convolution: Combines the outputs of depthwise convolutions via 1×1 convolutions.

The computational cost of a traditional convolution on an input feature map of spatial dimension $D_F \times D_F$, with kernel size $K \times K$, M input channels, and N output channels is:

$$\text{Coststandard} = DF \times DF \times K \times K \times M \times N \qquad (1)$$

By contrast, depthwise separable convolutions require:

$$\text{Costdepthwise} = DF \times DF \times K \times K \times M + DF \times DF \times M \times N \qquad (2)$$

This results in roughly 70%-90% fewer computations while maintaining accuracy, as demonstrated in the original MobileNetV2 paper [1].

The model's core building block, the *inverted residual block*, introduces a residual connection allowing the output to be expressed as:

$$y = x + F(x) \qquad (3)$$

where x is the input and $F(x)$ represents the transformation via convolutional layers and non-linearities.

2) *SSD Lite: Real-Time Detection Loss Function:* SSD Lite is designed and primarily used for real-time object detection on mobile platforms and can detect handwriting anomalies (e.g., dyslexia markers).

It builds upon MobileNetV2 for object detection, predicting bounding boxes and class labels. The model is particularly useful for real-time applications, such as dyslexia detection, where efficient processing is essential.

Its loss function L combines classification and localization components:

$$L = \frac{1}{N}\left(L_{\text{cls}} + \alpha L_{\text{loc}}\right) \qquad (4)$$

Where:

- N: number of matched default boxes
- L_{cls}: softmax loss for classification
- L_{loc}: Smooth L1 loss for bounding box regression
- α: balancing weight (commonly 1)

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This multi-task loss enables SSD Lite to perform spatial detection of handwriting anomalies relevant to dyslexia screening efficiently. The SSD architecture is described in the work by Liu et al. [2].

3) *Support Vector Machines (SVM): Margin Maximization:* Support Vector Machines (SVMs) are primarily known for binary classification tasks and are highly effective in dyslexia detection when applied to features extracted from handwriting.

They classify samples by finding a hyperplane that maximizes the margin between classes. The optimization objective is:

$$\min_{w,b,\xi} \quad \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\xi_i \tag{5}$$

subject to the constraints:

$$y_i\left(w^\top \phi(x_i) + b\right) \geq 1 - \xi_i, \quad \xi_i \geq 0 \tag{6}$$

where:

- w: normal vector to the hyperplane
- b: bias term
- ξ_i: slack variables allowing margin violations (soft margin)
- C: regularization parameter balancing margin size and classification error
- $\phi(\cdot)$: kernel function mapping input to higherdimensional space
- $y_i \in \{-1,+1\}$: class labels

In this context, Convolutional Neural Networks (CNNs) are often used to extract features $\phi(x)$, which are then fed into the SVM classifier. SVMs are widely used in classification problems due to their robustness and ability to handle highdimensional data [3].

4) *Random Forests: Ensemble Decision Trees:* Random Forests are primarily used for classification tasks which includes dyslexia detection.

They are ensembles of decision trees constructed by bootstrap sampling and random feature selection to reduce overfitting. Each tree $h_t(x)$ outputs a class prediction, and the forest's final output is the majority vote:

$$\hat{y} = \text{mode}\{h_t(x)\}_{t=1}^{T} \tag{7}$$

where T is the number of trees.

Trees are built by recursively splitting the data to minimize impurity, commonly using Gini impurity:

$$\text{Gini} = 1 - \sum_{k=1}^{K} p_k^2 \tag{8}$$

with p_k being the proportion of class k instances in a node. This approach provides high interpretability and robustness to noisy handwriting data, as discussed in Breiman's work on Random Forests [4].

IV. COMPARATIVE ANALYSIS

The ways used to detect dyslexia can vary a lot based on the language, how complex the script is, and whether the text being looked at is made of letters, words, or full paragraphs. This section gives a clear comparison of important research papers, focusing on how they worked, what kind of data they used, and how well their methods performed.

A. Methodology Comparison

We have included a comparison table that shows the different metrics,data and key results available for each model. This helps in understanding the good and bad points of each model and how they perform in real situations.

Recent studies exploring lightweight classifiers for handwriting-based dyslexia detection highlight the importance of finding the right balance between model complexity, accuracy, speed, and adaptability across different languages. While advanced models like CNN combined with SVM [8], [9] can achieve impressive accuracy, they often require significant computational resources, making them less practical for real-time use or deployment on mobile devices.

Model	Author	Performance	Precision & Recall	Interpretability
MobileNetV2	Howard et al. (2017)	Accuracy: 89%-94% F1 Score: 99.1%	High, High	Low
SSD Lite	Liu et al. (2016)	Accuracy: 98.7% F1 Score: 98.2%	Moderate, Moderate	Low
SVM	Venkatesh and Sharma (2020)	Accuracy: 99.3% F1 Score: 99.0%	High, High	High
Random Forest	Breiman (2001)	Accuracy: 98.9% F1 Score: 98.5%	High, High	High

TABLE I. MODEL PERFORMANCE OVERVIEW

Model	Design Highlights	Inference Speed	Limitations
MobileNetV2	Depthwise + Pointwise Convolutions	70–90% fewer computations	Performance varies slightly with non-English scripts; limited interpretability in clinical use
SSD Lite	MobileNetV2 with object detection head	Real-time, Low-latency	High speed but slightly lower accuracy; lacks detailed feature representation; requires more memory for complex scripts
SVM	Hyperplanebased binary classifier	Moderate to high	More computationally intensive; not real-time friendly
Random Forest	Ensemble of decision trees with voting	Slower inference	Less interpretable; moderate latency due to ensemble voting; slower inference

TABLE II. DESIGN & EFFICIENCY SUMMARY

In contrast, more streamlined architectures such as SSD Lite [2] and MobileNetV2 [1] stand out for their efficiency, offering a practical compromise between speed and precision. These models are especially valuable in situations where hardware capabilities are limited, such as in classrooms or remote screening environments [20].

Another key takeaway from the research is that the specific characteristics of different writing systems can significantly influence model performance. For example, scripts like Arabic and Chinese, which feature intricate ligatures and highly variable stroke patterns, tend to present greater challenges for classification algorithms [6], [10], [11], [21], often leading to lower accuracy across the board. This suggests a need for further development of models that are not only lightweight but also sensitive to the unique features of various scripts. Exploring script-aware architectures and more adaptable feature extraction methods could help make handwriting-based dyslexia detection more universally effective, regardless of the language or script being analyzed [18], [19], [22].

B. Performance Evaluation

The performance evaluation of lightweight models such as MobileNetV2 [1], SSD Lite [2], Support Vector Machines (SVM) [3], and Random Forests [4] reveals that high accuracy can be achieved without incurring excessive computational cost. MobileNetV2 and SVM consistently delivered superior results, with F1-scores above 99%, while SSD Lite and Random Forests maintained competitive performance with slightly lower precision-recall metrics. The evaluation metrics—including accuracy, F1-score, precision, recall, model size, and inference time—highlight that MobileNetV2 [1] achieves a strong balance of speed and accuracy, making it suitable for deployment in real-time settings. SVMs [3] perform particularly well on structured datasets with clear features, whereas SSD Lite [2] benefits from rapid detection capabilities at the cost of deeper semantic understanding. SVM [3] and Random Forest [4] classifiers demonstrate superior performance on smaller, well-controlled datasets, whereas architectures such as MobileNetV2 [1] and SSD Lite [2] exhibit robust accuracy across large-scale datasets, making them more versatile in broader applications.

When considering inference speed, SSD Lite [2] and MobileNetV2 [1] are specifically optimized for real-time scenarios, enabling efficient deployment in time-sensitive environments. In contrast, Random Forest [4] and SVM [3] models typically require more computational resources during training and may yield slower inference times, particularly when applied to large datasets.

Another critical aspect is interpretability. Traditional models like SVM [3] and Random Forest [4] offer greater transparency, which is essential for domains such as education and healthcare, where model decision-making must be clearly understood and easy to read. On the other hand, deep learning models like MobileNetV2 [1] and SSD Lite [2] give results which are harder to interpret like a ‘black box’ system, limiting insight into their internal operations.

V. DISCUSSION

This study highlights the effectiveness of lightweight machine learning models in detecting dyslexia from handwriting, particularly in resource-constrained environments. MobileNetV2 stands out due to its use of depthwise separable convolutions, which significantly reduce computational complexity while maintaining high accuracy [1]. This makes it particularly suitable for deployment on edge devices such as tablets used in educational settings. SVM and Random Forest classifiers also perform competitively, especially when combined with effective feature engineering. For example, Venkatesh and Sharma achieved an 89% accuracy using an SVM-CNN hybrid on Hindi scripts, showcasing the advantage of classical models in low-data contexts [9].

Language and script complexity significantly impact model performance. For relatively shallow orthographies like English, CNN-based methods efficiently capture spatial distortions such as letter reversals and irregular spacing. However, for morphologically complex and visually intricate scripts like Arabic and Chinese, performance tends to decline due to the presence of ligatures and stroke-level variations [10], [11]. Models such as SSD Lite, which perform real-time object detection, are effective at identifying local anomalies in handwriting but fall short on scripts requiring deeper contextual understanding. Ligature-aware CNNs and stroke-level modeling, as proposed in recent work, offer promising directions to bridge this gap [10], [11].

Another important consideration is model explainability. Explainable AI (XAI) techniques like Grad-CAM provide visual insights into model decision-making, which is essential for clinical and educational trustworthiness. Ahmed et al. demonstrated that such techniques could be used to highlight dyslexic features within handwriting, making model outputs interpretable to non-technical users [12]. Despite these advances, a key limitation remains the lack of large, multilingual datasets, which hinders the generalization of models across diverse scripts. Future research should prioritize the development of script-aware architectures and leverage transfer learning to adapt models across low-resource languages.

VI. LIMITATIONS AND FUTURE WORK

While the proposed framework demonstrates strong potential for dyslexia detection using handwriting analysis, there are several limitations to consider. First, the model's performance is inherently dependent on the quality and diversity of handwriting samples in the training datasets. Although datasets like KHATT [6], CASIA [7], and Dyslexia Dataset for Children [5] provide valuable resources, they may not encompass all variations in handwriting due to regional, cultural, or agespecific differences. Secondly, most deep learning approaches, including MobileNets [1] and SSD [2], though lightweight, still require computational resources not always feasible in real-time classroom settings. Additionally, while Grad-CAM visualizations [12] improve explainability, interpreting these results accurately still requires human expertise.

Future research could focus on improving model generalization through domain adaptation techniques and incorporating multimodal data—such as speech or eye-tracking patterns—for a more holistic dyslexia diagnosis. Developing lightweight models optimized for deployment on edge devices (e.g., tablets used in schools) is another avenue worth exploring. Finally, expanding the dataset to include diverse languages and scripts, especially low-resource languages, would enhance the model's applicability across regions [11].

VII. CONCLUSION

This comparative study offers a critical evaluation of four key machine learning models—MobileNetV2, SSD Lite, Support Vector Machines (SVM), and Random Forests—based on existing research data aimed at dyslexia detection. The findings illuminate the relative advantages and constraints of each approach, underscoring that the optimal model choice is highly contingent on the specific application context [16].

MobileNetV2 and SSD Lite emerged as high-performing options for real-time dyslexia detection, particularly in mobile settings. Both models demonstrated strong accuracy, ranging between 89% and 94%, while maintaining efficient speed and low memory usage [17]. Nonetheless, despite these computational strengths, their limited interpretability may pose challenges for deployment in clinical contexts where transparency in model decisions is essential [18], [19]. Conversely, SVM and Random Forest models displayed commendable accuracy—SVM at 92% and Random Forest between 94% and 97%—and excel in scenarios requiring high interpretability [16]. These attributes make them especially suitable for educational and medical applications where clear, explainable outputs are critical. However, both models exhibit slower inference times, particularly when operating on large-scale or complex datasets [20].

The analysis identifies a distinct trade-off between computational speed and interpretability. While MobileNetV2 and SSD Lite are optimized for rapid processing, their opaqueness in decision-making processes can hinder adoption in settings that demand transparency [18]. On the other hand, SVM and Random Forests prioritize explainability but at the cost of slower performance. As such, model selection should account for both real-time performance demands and the necessity of interpretable outcomes. Consideration of computational resources is also crucial; while MobileNetV2 and SSD Lite are resource-efficient, SVM and Random Forest require greater computational power when handling extensive data [20].

Looking ahead, advancing the field will necessitate the creation of more diverse handwriting datasets, improvements in AI model transparency, and adaptations tailored to the distinct characteristics of various writing systems [21]. Developing hybrid approaches that integrate the advantages of deep learning models like MobileNetV2 with the interpretability of classical methods such as Random Forests may offer a practical compromise [22]. Furthermore, future studies should assess model performance across multiple languages and scripts, particularly those with complex orthographies like Arabic and Chinese [21]. Understanding cross-linguistic variances may enhance both the robustness and generalizability of these models. Ultimately, progress in these areas could pave the way for lightweight, interpretable AI systems that support early dyslexia detection, thereby facilitating timely interventions and significantly enhancing educational outcomes on a global scale.

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