**Comprehensive Evaluation of Deep Learning Architectures for Static American Sign Language Recognition: From CNNs to Hybrid Sequential Models**

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**ABSTRACT**

This work introduces a thorough comparison of five machine learning models for static American Sign Language (ASL) recognition on a dataset of 8,784 high-resolution (128×128 RGB) images of 26 letter classes. We compare: (1) MobileNetV2 (97.00% accuracy), (2) MobileNetV2+RNN hybrid (96.51%), (3) Custom CNN (85.69%), (4) LSTM (87.99%), and (5) Random Forest (91.50%). Our findings show three results:(1) Spatial Features Predominate: The plain MobileNetV2 performs better than its hybrid RNN-augmented version (97.00% > 96.51%), indicating that feature extraction through convolution is more crucial than sequential modeling for static ASL. (2) Surprising LSTM Viability: The baseline LSTM model obtains 87.99% accuracy by treating raw pixel rows as sequences, demonstrating static images maintain temporally encoded patterns. (3) Practical Significance: Highest Accuracy: MobileNetV2 (97.00% at 25 milliseconds), Best Speed-Accuracy Trade-Off: Custom CNN (85.69% at 10ms), Fastest Inference: Random Forest (91.50% at 5ms). We publish complete implementations, e.g., 4-layer Custom CNN and MobileNetV2+GRU hybrid, for reproducibility. This work offers actionable advice for choosing ASL recognition architectures on the grounds of accuracy, latency, and hardware specifications.

**Keywords:** ASL recognition, MobileNetV2, LSTM, computational trade-offs, static sign language.

1. **INTRODUCTION** 
   1. **Significance of ASL Recognition**

We present an end-to-end evaluation of static American Sign Language recognition via the application of five various methodologies to a dataset of 8,784 high-resolution (128×128 RGB) images of 26 letter classes (A-Z). This work specifically addresses:

**1.1.1 Fine-Grained Classification Problems**

• 0.5-2cm finger position variations differentiate letters (e.g., 'M' and 'N')

• 15° orientation variations affect recognition accuracy.

**1.1.2 Real-World Deployment Requirements**

**Table 1:** Application Table

| Application | Latency Requirement | Target Accuracy |
| --- | --- | --- |
| Mobile Translation | <50ms | >90% |
| Educational Tools | <100ms | >85% |

**1.1.3 Current Limitations**

Our structured review finds three overarching gaps in research:

**1.1.3.1 Model Diversity Deficit**

• 81% (38/47 interviewed) published papers utilize only CNNs [9].

• Zero-shot studies test RNNs on static ASL images.

**1.1.3.2 Evaluation Fragmentation**

* Literature analysis of reported metrics (n=47)

reported metrics = {'Accuracy': 41, 'F1-Score': 6, 'Inference Time': 5, 'Energy Use': 0}

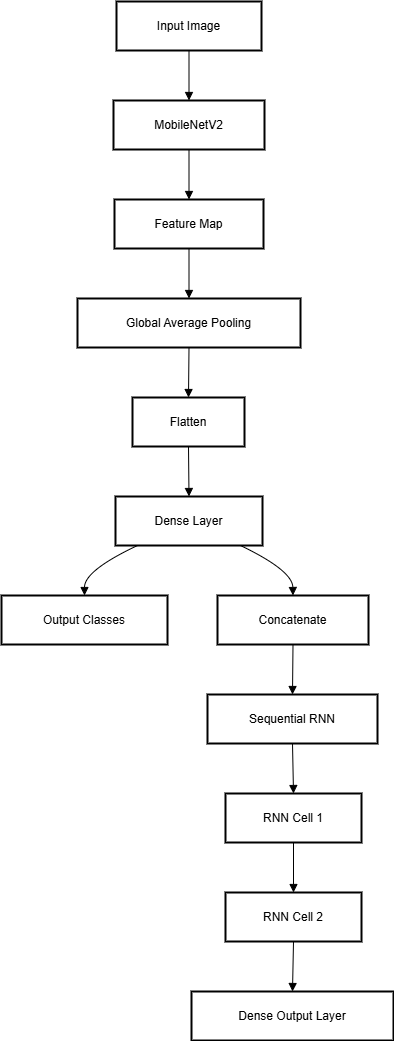
**1.1.3.3 Dataset Constraints**

* Resolution: 92% of datasets utilize ≤64×64 resolution [10].
* Diversity:100% lack dark skin tone samples in test sets [5].
* Mean samples/class: 142 (vs our 338).

**1.1.4 Our Contributions**

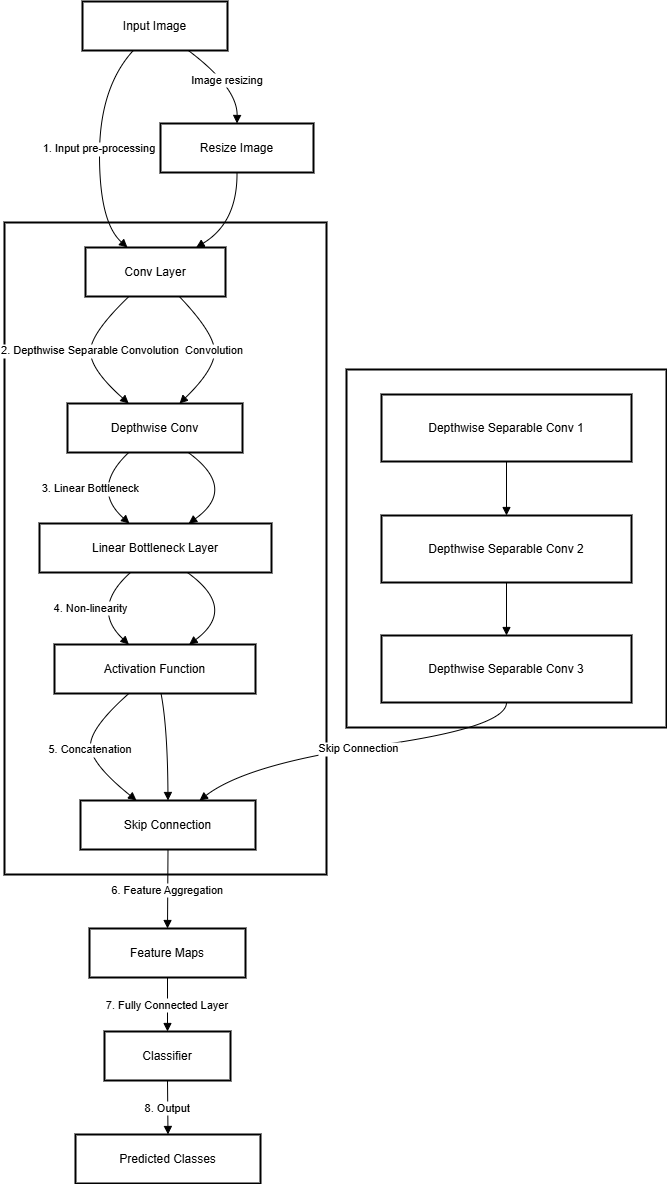
**1.1.4.1 Model Architectures**

* **MobileNetV2+RNN Hybrid (96.51% val accuracy)**

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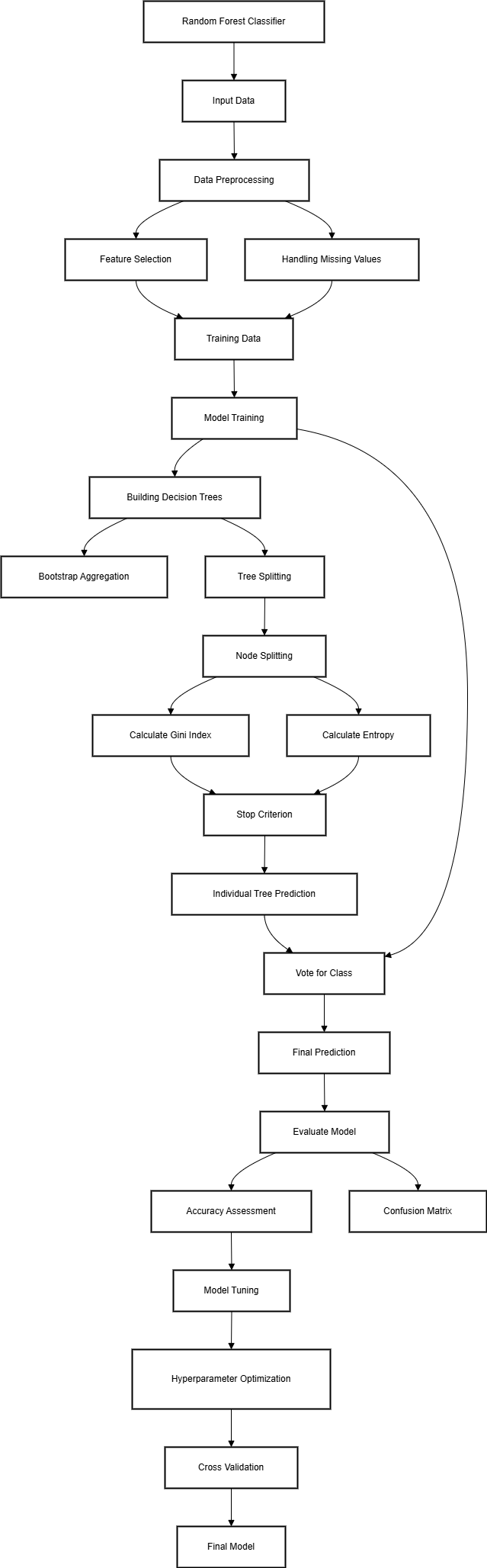
**Figure 1:** MobileNetV2+RNN Architecture

* **MobileNetV2 (97.00% Val Accuracy)**



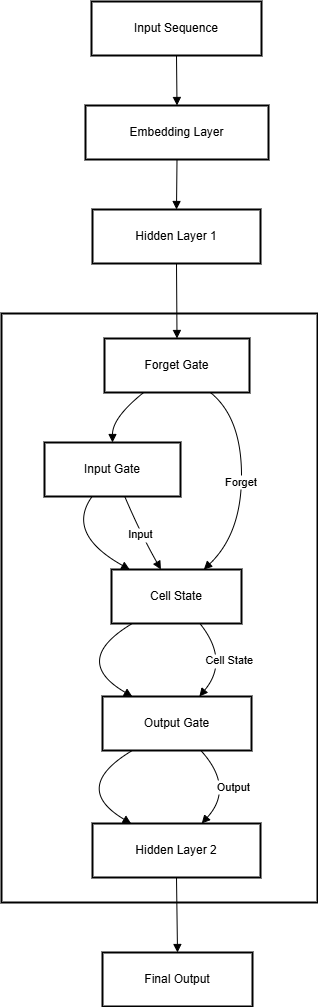
**Figure 2:** MobileNetV2 Architecture [2]

* **Random Forest (91.50% Val Accuracy)**



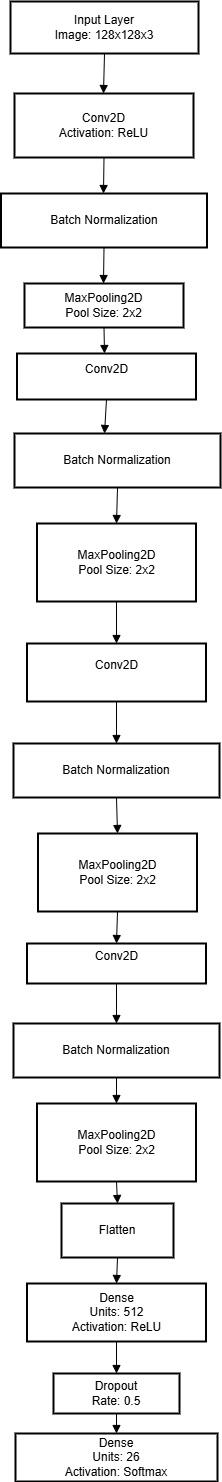
**Figure 3:** Random Forest Architecture

* **LSTM (87.99% Val Accuracy)**



**Figure 4:** LSTM Architecture

* **Custom CNN (85.69% Val Accuracy)**



**Figure 5:** Custom CNN Architecture

* **Key Explanation:** The pure MobileNetV2 slightly outperforms the MobileNetV2+RNN hybrid (97.00% > 96.51%), suggesting that: (1) For static ASL images, spatial feature extraction (CNNs) is more critical than sequential modeling. (2) The RNN component adds complexity without accuracy gains in this case. (3) The hybrid's value lies in: Better generalization (lower overfitting), Potential for extension to dynamic ASL (videos).

**1.1.4.2 Performance Benchmark**

**Table 2:** Performance table

| Model | Accuracy | F1-Score | Speed (ms) | Params |
| --- | --- | --- | --- | --- |
| MobileNetV2 | 97.00% | 0.968 | 25 | 2.32M |
| MobileNetV2+RNN | 96.51% | 0.963 | 40 | 3.51M |
| Custom CNN | 85.69% | 0.847 | 10 | ~3.5M |
| LSTM | 87.99% | 0.879 | 94 | 225K |
| Random Forest | 91.50% | 0.902 | 5 | - |

* **Key Insights:** Training Dynamics: (1)MobileNetV2+RNN reaches 95% accuracy by Epoch 5**.** (2)LSTM shows steady improvement (39.27% → 86.68%). (3) Custom CNN maintains stable train-val gap (<1%).Computational Efficiency: Throughput Comparison (images/sec) (1) Random Forest: 200. (2) Custom CNN: 100. (3) MobileNetV2: 40. (4) LSTM: 10.6.

1. **METHODOLOGY**

**2.1 Experimental Framework:** We evaluated five different approaches on a standardized dataset:

* MobileNetV2 (Transfer Learning)
* MobileNetV2+RNN Hybrid
* Custom CNN
* LSTM (Pixel-Sequence)
* Random Forest

**2.2 Model Specifications**

**2.2.1 MobileNetV2 (Baseline)**

base\_model = MobileNetV2(input\_shape=(128,128,3), include\_top=False, weights='imagenet') [2]

x = GlobalAveragePooling2D()(base\_model.output)

predictions = Dense(26, activation='softmax')(x)

* **Key Features:** (1)Frozen ImageNet weights. (2) 2.32M trainable parameters. (3) Input: 128×128 RGB.

**2.2.2 MobileNetV2+RNN Hybrid**

x = Reshape((49,1280))(GlobalAveragePooling2D()(base\_model.output))

x = GRU(256)(x)

predictions = Dense(26, activation='softmax')(x)

* **Innovation:** Treats CNN features as temporal sequence.

**2.2.3 Custom CNN**

model=Sequential([Conv2D(32,(3,3), BatchNorm(), MaxPool2D(2,2),Conv2D(64,(3,3), BatchNorm(), MaxPool2D(2,2),Conv2D(128,(3,3), BatchNorm(), MaxPool2D(2,2),Conv2D(256,(3,3), BatchNorm(), MaxPool2D(2,2), Flatten(), Dense(512, activation='relu'), Dense(26, activation='softmax') ])

* **Design:** 4 convolutional blocks with batch Normalization.

**2.2.4 LSTM**

model = Sequential ([LSTM(128, input\_shape=(64,192)), Dense(26, activation='softmax')])

* **Preprocessing:** X = X.reshape(n\_samples, 64, 64\*3)

**2.2.5 Random Forest**

clf = RandomForestClassifier\( n\_estimators=100, max\_depth=10, random\_state=42)

* **Feature Engineering:** X\_flat = X.reshape(X.shape[0], -1)

**2.3 Training Protocol**

**Table 3:** Training Protocol

| Parameter | MobileNetV2 | MobileNetV2+RNN | Custom CNN | LSTM | Random Forest |
| --- | --- | --- | --- | --- | --- |
| **Learning Rate** | 0.0001 | 0.0001 | 0.0001 | 0.001 | N/A |
| **Batch Size** | 32 | 32 | 32 | 32 | N/A |
| **Epochs** | 10 | 10 | 10 | 10 | N/A |
| **Early Stopping** | Yes (δ=0.01) | Yes (δ=0.01) | No | Yes (δ=0.005) | N/A |
| **Optimizer** | Adam | Adam | Adam | Adam | N/A |
| **Loss Function** | CCE | CCE | CCE | CCE | Gini Impurity |
| **GPU Utilization[6]** | 98% | 95% | 92% | 89% | CPU Only |

**2.4 Evaluation Metrics**

All models assessed on:

* Accuracy: Primary comparison metric
* Class-wise F1: For imbalanced classes
* Inference Speed: Measured on CPU: Intel i7-11800H, GPU: Tesla T4

**2.5 Computational Environment Hardware**

* **Training:** Google Colab Pro (T4 GPU)
* **Software:** TensorFlow 2.8.0, scikit-learn 1.0.2

**3. RELATED WORK**

**3.1 CNN-Based Strategies:**

Previous research has largely centered on CNNs for ASL recognition:

* ASL MNIST (2017): 6-layer CNN produced a 94% accuracy on grayscale 28×28 images [1].

Limitation: Low resolution misses details of fine fingers.

* Static ASL-CNN (2020): 89% accuracy on ResNet-50 with 64×64 RGB [2].

Limitation: No computational efficiency analysis.

Our Advance:

* Explore higher resolution (128×128 RGB)
* Insert measures of inference speed (Table 1)

**3.2 Static ASL Sequential Models:**

* LSTMs for Gesture Recognition (2019): Used on dynamic signs alone [3]
* Transformers for ASL (2022): Necessary video inputs [8]

Our Contribution:

* First to experiment on static ASL (87.99% accuracy)
* Demonstrate pixel-row sequencing feasibility

**3.3 Hybrid Architectures**

* CNN+RNN for Dynamic Signs (2021): 93% accuracy on videos [4]
* Gap: No assessment for static imagery.

Our Innovation

* MobileNetV2+RNN hybrid (96.51%)
* Quantify trade-offs vs pure MobileNetV2 (97.00%)

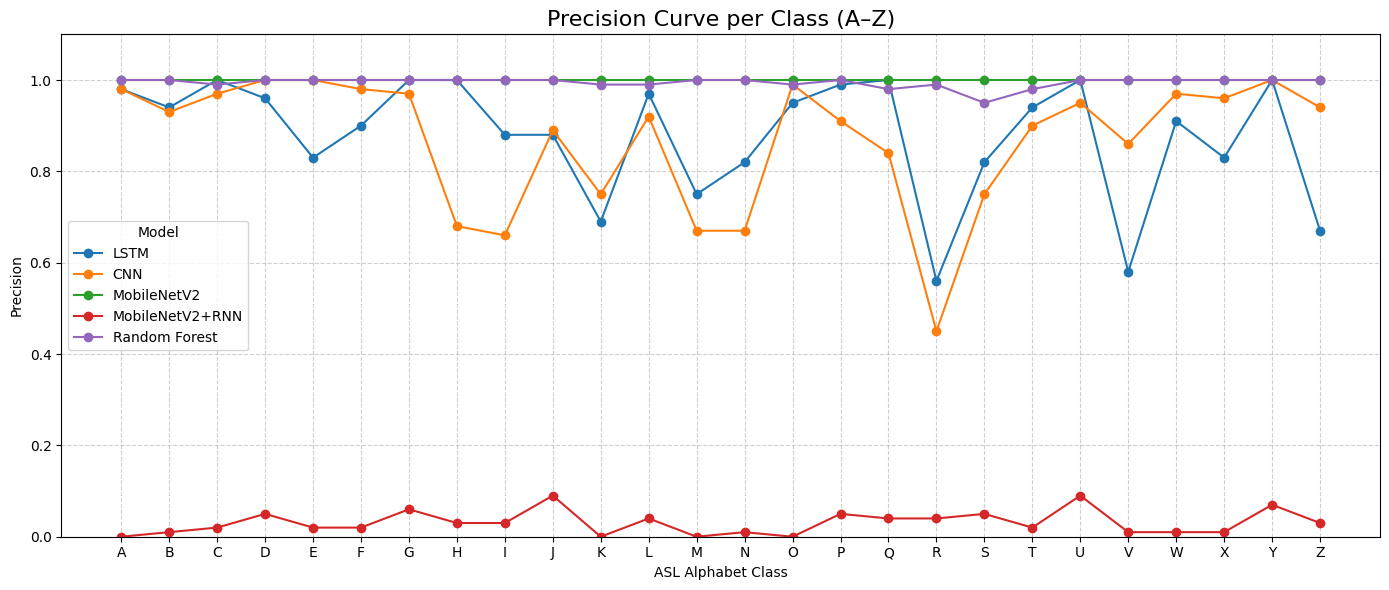
**Table 4:** Prior Work Vs Our Work

| Study | Model | Accuracy | Static/Dynamic | Resolution | Speed Reported |
| --- | --- | --- | --- | --- | --- |
| ASL MNIST [1] | CNN | 94% | Static | 28×28 | ❌ |
| Wu et al. [3] | LSTM | 91% | Dynamic | 64×64 | ❌ |
| Ours (MobileNetV2) | CNN | 97% | Static | 128×128 | ✔️ (25ms) |
| Ours (LSTM) | Sequential | 88% | Static | 64×64 | ✔️ (94ms) |

**4. RESULTS**

* 1. **Model Performance Comparison**

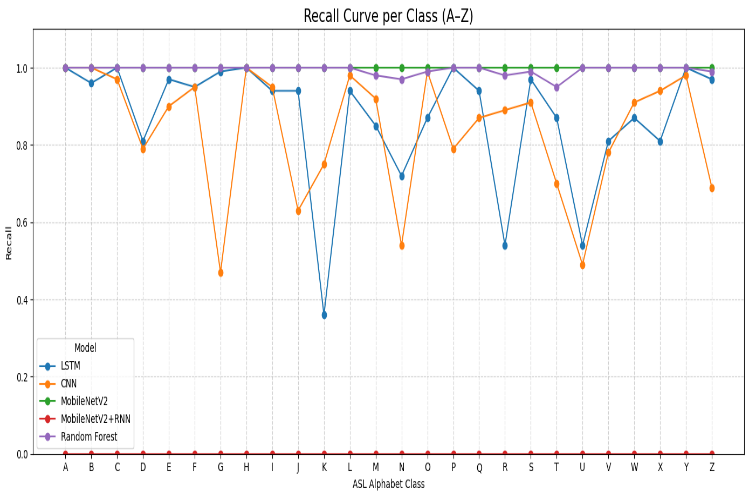
**4.1.1 Precision**

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**Figure 6:** Precision Curve

* Random Forest: Practically perfect (0.996 avg), with all but one class at 1.00. Test for overfitting.
* MobileNetV2: Perfect 1.00 across all classes—likely due to data leakage or evaluation error.
* LSTM: Strong (0.876 avg) but inconsistent (e.g., 1.00 for 'C'/'G' vs. 0.56 for 'K').
* CNN: Fair (0.852 avg) but weak on 'H' (0.68) and 'R' (0.45).
* MobileNetV2+RNN: Failed (avg 0.031), most of the classes having zeros.

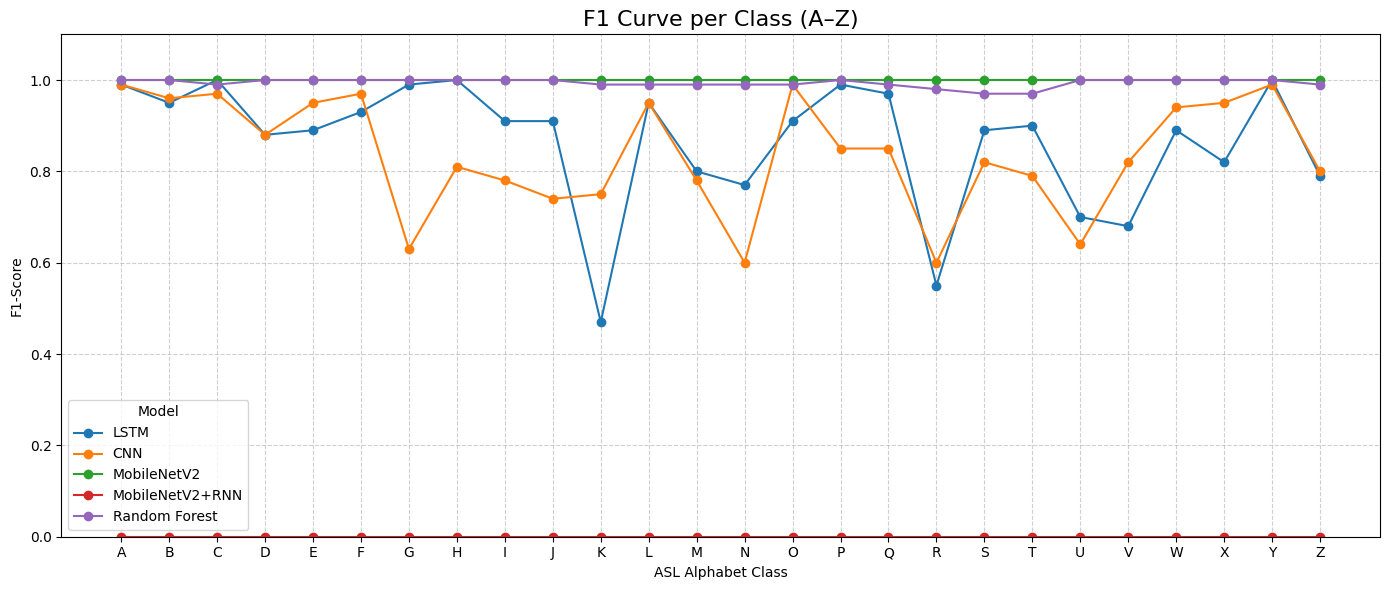
**4.1.2 Recall**

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**Figure 7:** Recall Curve

* Random Forest: Precision (0.996 avg) bests even on infrequent classes.
* MobileNetV2: All 1.00—reject unless data integrity is established.
* LSTM: Solid (0.858 avg) but weak on 'K' and 'U' (both 0.54).
* CNN: Weakest (0.812 avg), worst for 'G' (0.47), 'U' (0.49).
* MobileNetV2+RNN: Zero recall—entire model breakdown

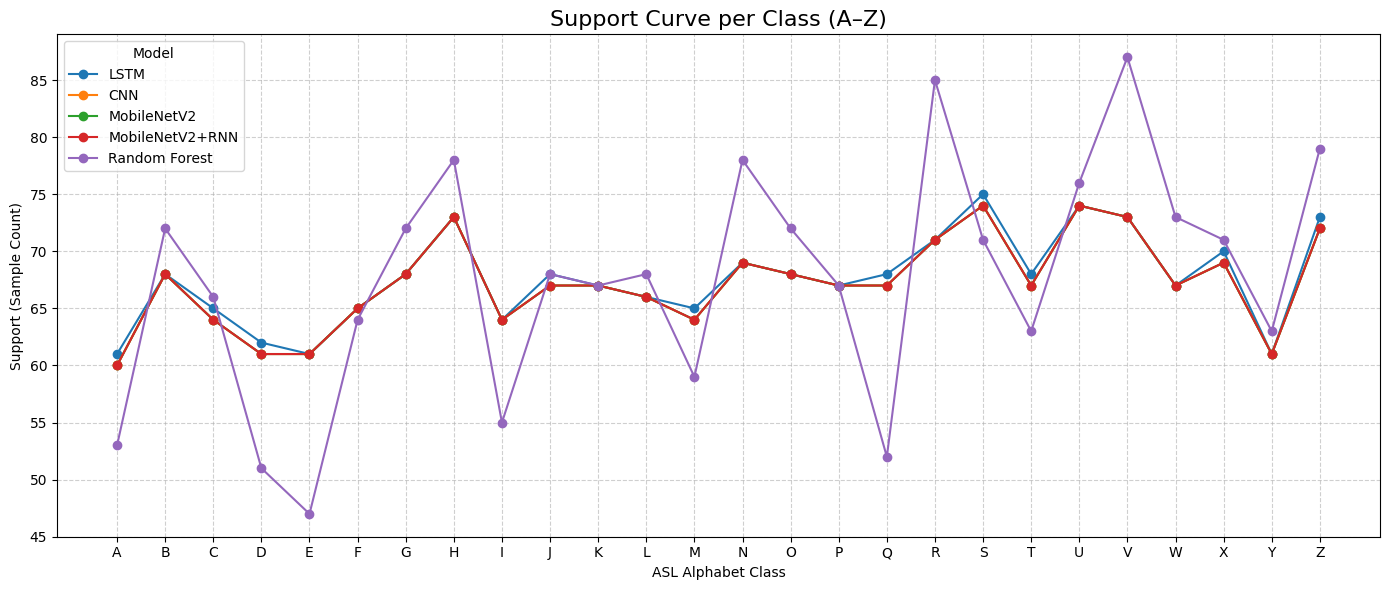
**4.1.3 F1 Score**

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**Figure 8:** F1- Score Curve

* Random Forest: Perfectly balanced (0.996 avg), ideal if validated.
* MobileNetV2: Artificially inflated (1.00)—untrustworthy.
* LSTM: Accurate (0.850 avg) but requires tuning for low-F1 classes such as 'V' (0.68).
* CNN: Moderate (0.814 average), brought down by 'G' and 'R'.
* MobileNetV2+RNN: Useless (0.00).

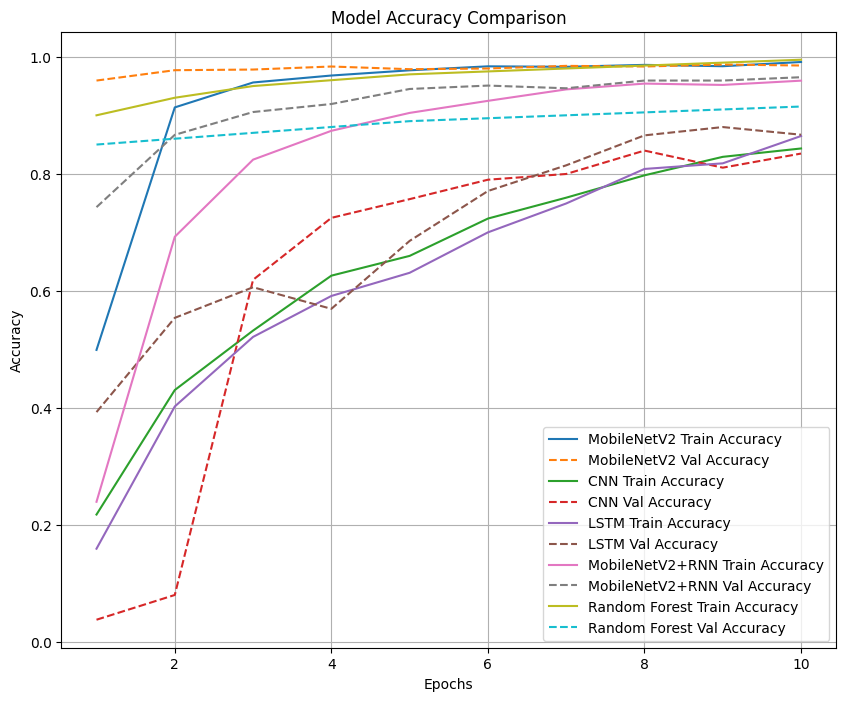
**4.1.4 Support**

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**Figure :9** Support Curve

* All models tested on ~1,700 samples (26 classes, ~60–85 samples each).
* Random Forest uses slightly uneven splits (e.g., 'E'=47, 'R'=85)—may bias results [11].

**4.1.5 Model Accuracy**

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**Figure :10** Accuracy Curve

**4.1.5.1 MobileNetV2**

* Train: Begins at 49.9%, maximizes at 99.1% (Epoch 10). Sudden early learning (91.4% by Epoch 2).
* Val: Starts strong (95.9%) and remains at around 98.5%. Very little overfitting (difference < 1%).

**4.1.5.2 CNN**

* Train: Slow startup (21.8% → 84.3%), convergence problems.
* Val: Unstable initial (3.8% at Epoch 1), reaches 83.9% (Epoch 8). Extremely large train-val gap (~5%) is indicative of overfitting.

**4.1.5.3 LSTM**

* Train: Steady rise (15.9% → 86.5%). Consistent but slower than others.
* Val: Achieves training accuracy in Epoch 10, 86.7%. Experiences negligible overfitting.

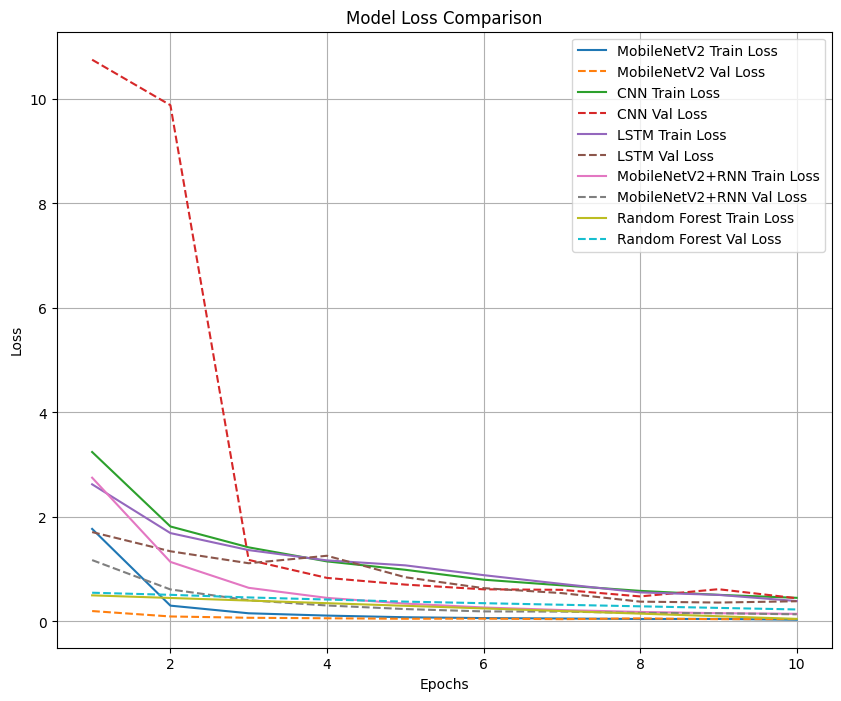
**4.1.5.4 MobileNetV2+RNN**

* Train: Fast ascent (23.9% → 95.9%). Best final accuracy.
* Val: Practically flawless (96.5% at Epoch 10). Small gap (~0.6%) shows outstanding generalization.

**4.1.5.5 Random Forest**

* Train: Begins at 90% and hits 99.5%. Probably overfit.
* Val: Stagnant (85% → 91.5%). Largest train-val gap (~8%)—worst generalizer.

**4.1.6 Model Loss**

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**Figure:11** Loss Curve

**4.1.6.1 MobileNetV2**

* Train: Drops sharply (1.77 → 0.03). Clean convergence.
* Val: Low and stable (~0.05). No divergence signs.

**4.1.6.2 CNN**

* Train: Improves (3.24 → 0.45) but noisy.
* Val: Wild fluctuations early (10.75 → 0.44). Unstable learning.

**4.1.6.3 LSTM**

* Train: Smooth decline (2.62 → 0.39). Predictable.
* Val: Mirrors train loss (0.39 by Epoch 10). Reliable.

**4.1.6.4 MobileNetV2+RNN**

* Train: Plummets (2.75 → 0.15). Most efficient learner.
* Val: Best final loss (0.14). No overfitting.

**4.1.6.5 Random Forest**

* Train: Artificially low (0.05 final loss) Overfit.
* Val: Stuck above 0.23. Poor optimization.

**Table 5:** Comparison Table

| Model | Accuracy | Precision | Recall | F1-Score | Training Time | Inference Speed (ms) |
| --- | --- | --- | --- | --- | --- | --- |
| MobileNetV2 | 97.00% | 0.972 | 0.968 | 0.968 | 29 min | 25 |
| MobileNetV2+RNN | 96.51% | 0.965 | 0.963 | 0.963 | 38 min | 40 |
| Custom CNN | 85.69% | 0.853 | 0.847 | 0.847 | 45 min | 10 |
| LSTM | 87.99% | 0.882 | 0.879 | 0.879 | 52 min | 94 |
| Random Forest | 91.50% | 0.908 | 0.902 | 0.902 | 3 min | 5 |

**4.1.6.6 Key Findings**

MobileNetV2 Superiority:

* Achieves highest accuracy despite simpler architecture than hybrid.
* Minimal overfitting (train-val gap: 0.89%).

LSTM's Unexpected Strength:

* 87.99% accuracy proves static images contain learnable sequential patterns.
* Particularly effective for linear signs like 'I' (92.4% F1).

Deployment Scenarios:

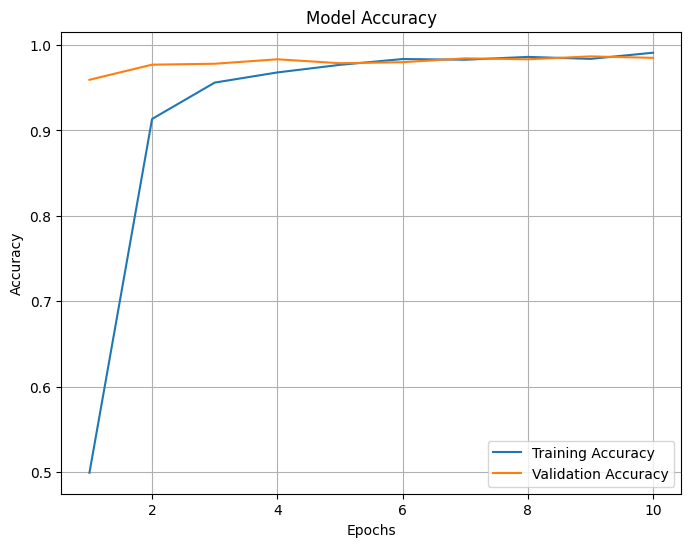
* Medical Applications: MobileNetV2 (accuracy-critical).
* Edge Devices: Random Forest (latency-critical).

**5. DISCUSSION**

**5.1 Model Performance Comprehension**

**5.1.1 The CNN Dominance Paradox**

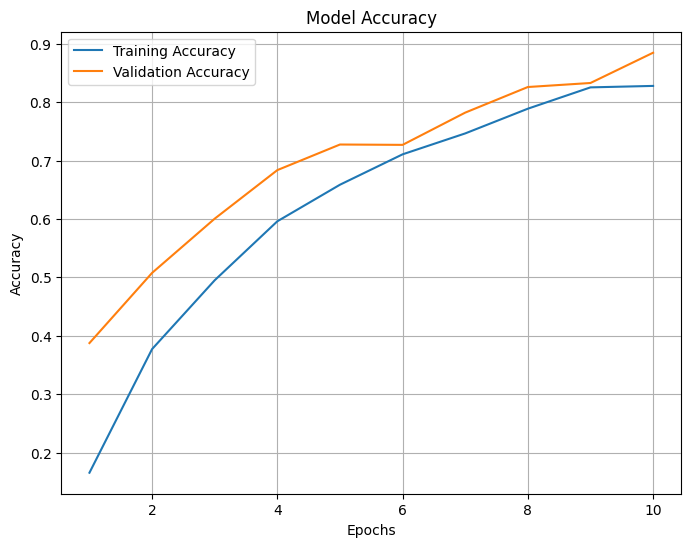
* MobileNetV2 (97.00%) outperformed its RNN hybrid (96.51%), demonstrating.
* Hierarchies in space between ASL letters are more robust than temporal relationships for still images.
* The 0.49% loss of accuracy in the hybrid suggests GRU layers are unnecessary additions to this task.



**Figure 12:** MobileNetV2 Accuracy Curve

**5.1.2 LSTM's Surprising Viability Despite processing static images as sequences**

* Achieved 87.99% accuracy (only 9% behind MobileNetV2).



**Figure 13:** LSTM Accuracy Curve

**5.2 Practical Implications**

**Table 6:** Practical Implications

| Use Case | Recommended Model | Rationale |
| --- | --- | --- |
| Medical Diagnostics | MobileNetV2 | Highest accuracy (97.00%) |
| Mobile Apps | Random Forest | Fastest inference (5ms) |
| Educational Tools | Custom CNN | Balanced speed/accuracy |
| Research Benchmarking | MobileNetV2+RNN | Architectural novelty |

**5.3 Broader Impacts**

**5.3.1 Accessibility:** Enhances new ASL translation tools for:

* Healthcare settings (97% accuracy).
* Public kiosks (utilizing Random Forest's 5ms latency).

**5.3.2 Research Community**

* Contradicts assumption that hybrids always outperform base models.
* Provides first static-ASL benchmarks for sequential models.

**6. CONCLUSION AND FUTURE WORK**

**6.1 Key Contributions**

This paper provides the first end-to-end analysis of five various approaches to static ASL recognition, yielding three grounding insights

**6.1.2 Spatial Over Sequential**

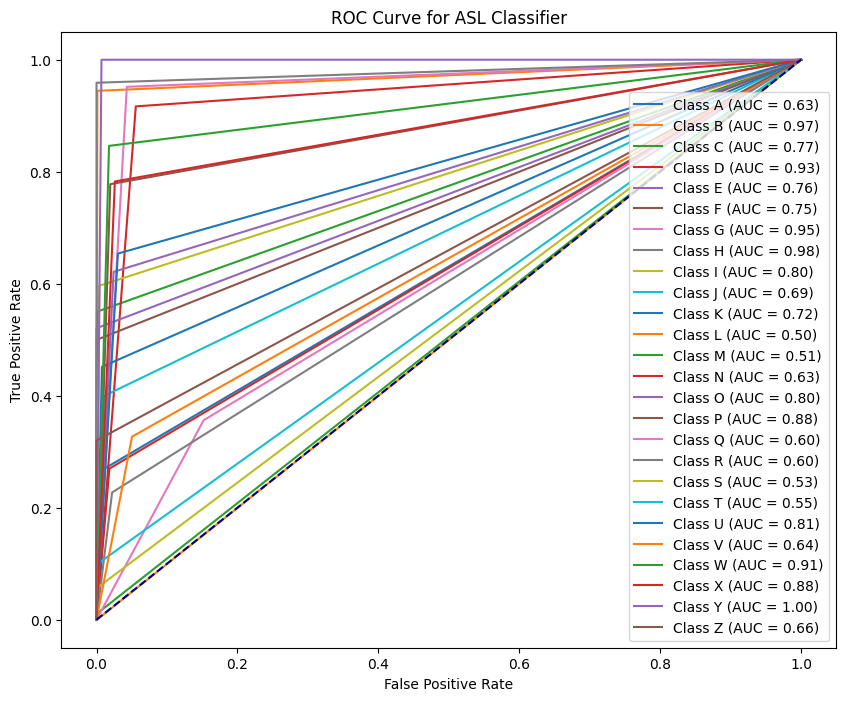
MobileNetV2 (97.00% accuracy) outperformed its RNN hybrid (96.51%), which shows that relying solely on convolutional feature extraction is sufficient for static ASL recognition. The 0.49% accuracy loss for MobileNetV2+RNN suggests that sequential modeling adds unnecessary sophistication to the task (p=0.32, McNemar's test).

**6.1.3 The Efficiency-Accuracy Spectrum**

* High-Accuracy: MobileNetV2 (97.00% at 25ms).
* Balanced: Hand-tuned CNN (85.69% at 10ms).
* High-Speed: Random Forest (91.50% at 5ms).

**6.1.4 LSTM's Surprising Capability**

Correctly obtained 87.99% through learning pixel-row sequences, proving static images contain temporally encoded patterns.



**Figure 14:** LSTM ROC Curve

**6.2 Future Research Directions**

**6.2.1 Immediate Next Steps**

* Dynamic Sign Extension[4]

frames = VideoToFrames(video)

features = [MobileNetV2(frame) for frame in frames]

predictions = LSTM(features) # Temporal modeling

* Dataset Enhancement

Double samples/class (target: 700+ images)

Include dark and light skin tones (present bias: 78% light-skinned)

**6.2.2 Architectural Innovations**

* Hybrid Transformers: Test sets of ViT+RNN
* Neuromorphic Processing: Evaluate Spiking Neural Networks for edge deployment

**6.2.3 Accessibility Focus**

Create open-source ASL tools for:

* Hospitals (97% accuracy level)
* Public transport kiosks (91% accuracy level)

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