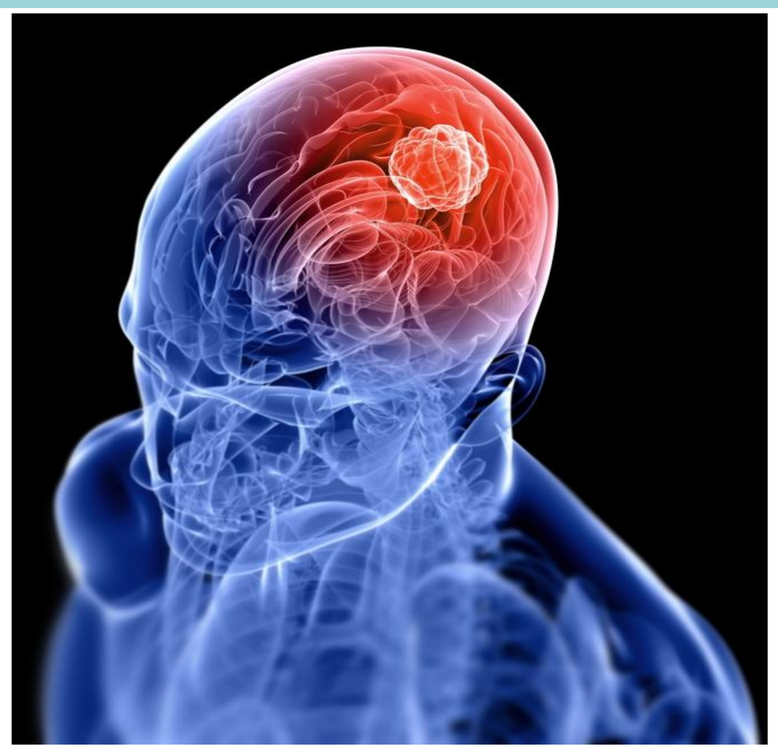
A deep Learning Model for Brain Tumor Segmentation

Tazkia Mim Angona and Dr. Md. Rubaiyat Hossain Mondal

Brain Tumor



Brain tumors arise in the central nervous system due to abnormal cell respiration and proliferation. **Effective diagnosis and treatment planning** depends on identifying the **brain tumor areas from MRI** images accurately. **Manual brain tumor segmentation** is **time-consuming** and **prone to errors**, necessitating automated solutions for improved efficiency and accuracy.

Literature Review

- **U-Net**'s variants, **S3D-Unet** [Chen et al. 2019]**, HI-Net** [Qamar et al. 2021], and **dResU-Net** [Raza et al. 2023] improved segmentation by leveraging **multi-scale features.**
- **Transformer-based models [**Wenxuan et al. 2021, Hatamizadeh et al. 2021] **captured long-range dependencies,** overcoming CNNs limitations**.**
- Despite these advancements**,** 3D brain tumor segmentation remains challenging due to **variations in tumor size, shape, and location.**

Research Contribution

We propose **3D ResAttU-Net-Swin**, a hybrid model combining residual U-Net, attention mechanisms, and 3D Swin Transformer. The model –

- Effectively **captures both fine-grained and global features** from 3D MRI scans.
- **Enhances segmentation accuracy** and robustness, **addressing limitations of 2D patch-based models**.
- **Bridges the gap** between **CNN- and transformer-based models** for improved brain tumor segmentation.

BraTS Dataset

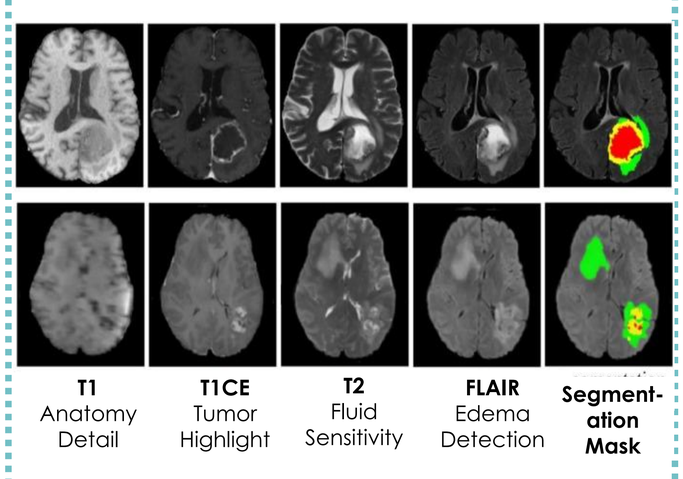


Fig: Sample MRI images with their ground truth for all modalities (green for Edema, red for Necrosis, and yellow for Enhancing tumor).

- 3D Scans Multimodal MRI with shape – 240 × 240 × 155
- Tumor regions:
  - Tumor Core (TC) – Necrosis + Enhancing Tumor
  - Whole Tumor (WT) – Necrosis + Enhancing Tumor + Edema
  - Enhancing Tumor Core (ET) – Active Tumor Region

Proposed Solution

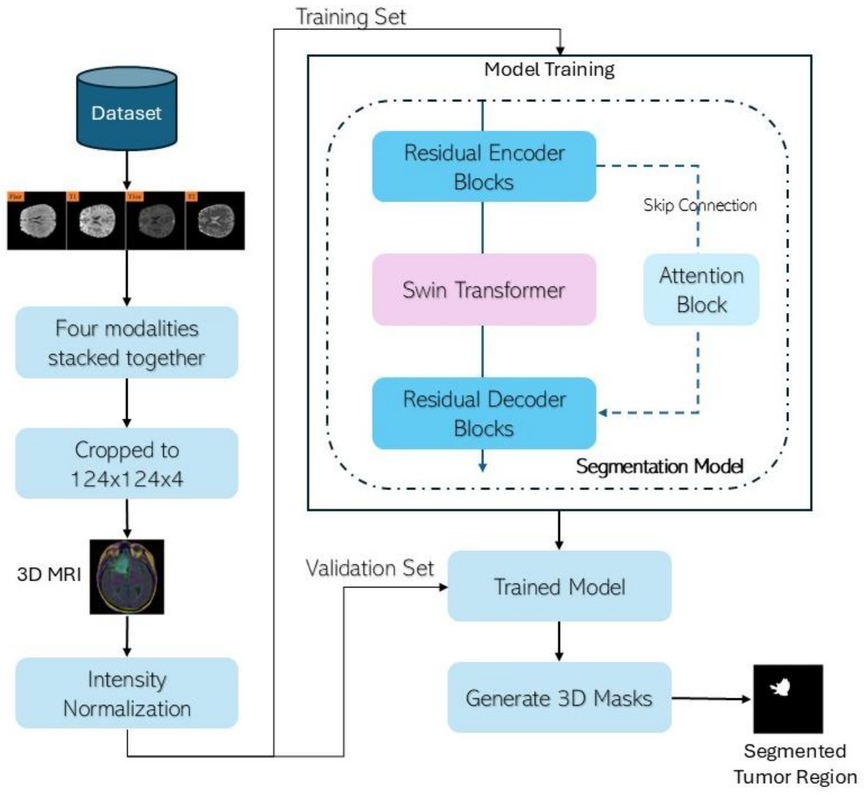
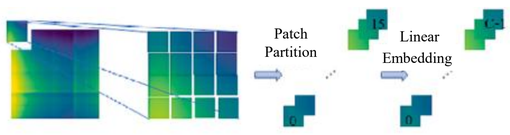


Fig: Simplified Conceptual Model of Proposed ResAttU-Net-Swin Framework

The Proposed Model

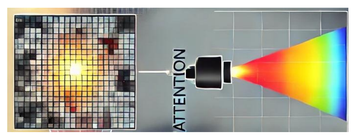
- The proposed hybrid model, ResAttU-Net-Swin is able to deal with 3D images directly and improves segmentation accuracy by extracting both low- and high-level features effectively from brain MRI images.
- 4 level encoder and decoder blocks with residual connections enhance feature learning and address the vanishing gradient problem.
- Attention based skip connections encourage feature recovery while narrowing the semantic gap between the encoder and decoder.
- A 3D Swin Transformer is introduced in this model to capture long-range dependencies, which is necessary for precise segmentation of brain tumors of different sizes.

Framework Components



Swin Transformer – processes images in small patches and captures long-range dependencies for better feature extraction.

Residual U-Net – An advanced version of U-Net that uses residual (shortcut) connections to improve learning and prevent information loss.



Attention Method: A method that helps the model focus on important parts of the image while filtering out less relevant details.

Results

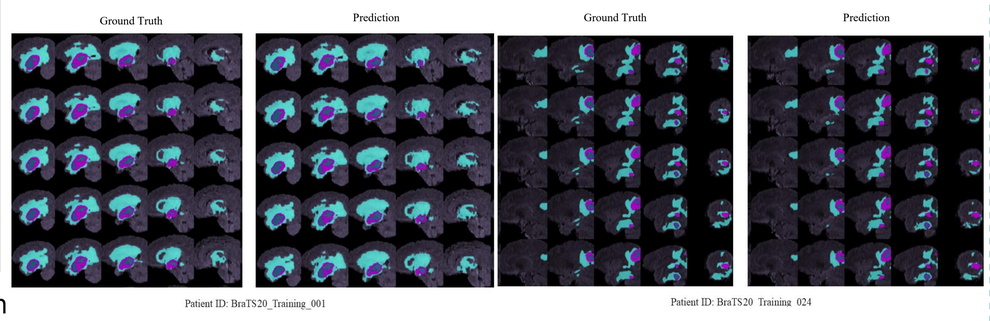
DSC Scores Comparative Analysis

Model Architecture	WT	TC	ET	Avg.
Residual U-Net [Raza et al. 2023]	0.866	0.836	0.800	0.834
UNet and Transformer pipelines in parallel [Soh et al. 2023]	0.900	0.836	0.783	0.840
Hybrid architecture of U-Net, V-Net and transformers [Aboussaleh et al 2024]	0.920	0.828	0.817	0.855
CNN-Transformer based encoders in U-Net [She et al. 2023]	0.908	0.864	0.832	0.868
Proposed Model	**0.925**	**0.897**	**0.826**	**0.883**

DSC (Dice Similarity Coefficient) – Measures overlap between predicted and actual tumor regions.

- Our model achieved an average DSC of 88.27% on BraTS 2020 dataset.
- The model effectively segments three tumor regions: Enhancing Tumor (ET), Tumor Core (TC), and Whole Tumor (WT).
- The performance comparison highlights that the ResAttU-Net-Swin model's robustness and effectiveness in brain tumor segmentation.

Sample results of predicted tumor regions



(WT: cyan, TC: navy blue, ET: magenta)

Conclusion

- The hybrid brain segmentation model improves segmentation, aiding in accurate and efficient tumor detection.
- The model can be adapted for real-time segmentation in clinical workflows, assisting radiologists in fast diagnoses.
- The hybrid approach can be extended to other organ segmentation, contributing to broader medical diagnostics.
- By expanding to larger multimodal datasets, the model can generalize to diverse medical imaging tasks.

Finger Joint Angle Estimation Methods for 3D Printed Hand In Computer Vision

Md. Azizul Hakim Bappy and Hossen A Mustafa

Abstract

Measurement of angle between finger-tip and wrist is a key challenge for robotic hands. This work reveals an effective angle measurement technique for robotic hands using a single RGB camera. Our distance-to-angle method, leveraging Mediapipe, dramatically outperforms complex trigonometric approaches in accuracy and speed. Achieving near-perfect angle estimation (MAE 1.77°), it unlocks and resource-efficient vision-based hand control that can challenge traditional reliance on complex calculations and hardware.

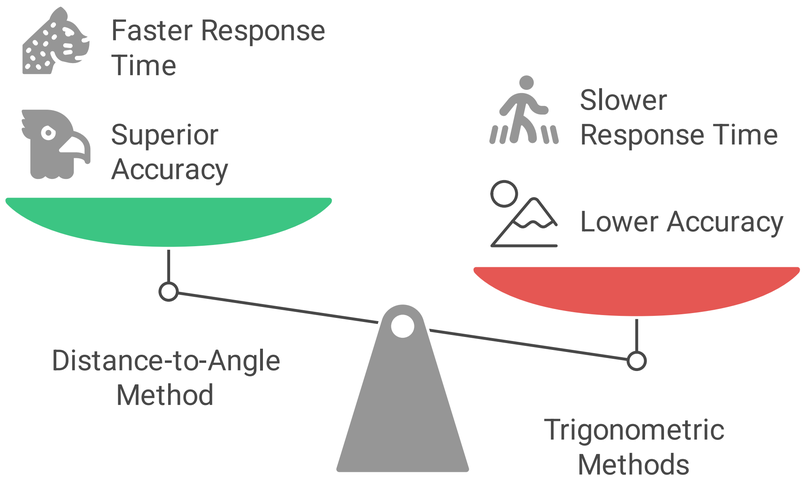
Background & Motivation

The problem:
- **Mimicking the human hand's intricate movements in robots is incredibly complex in computer vision due to the complexity in the finger joint angle calculation.**

Existing Solution:
- **Depth sensors, e.g., LiDAR, Time-of-Flight, etc., are often used, but add cost and complexity.**

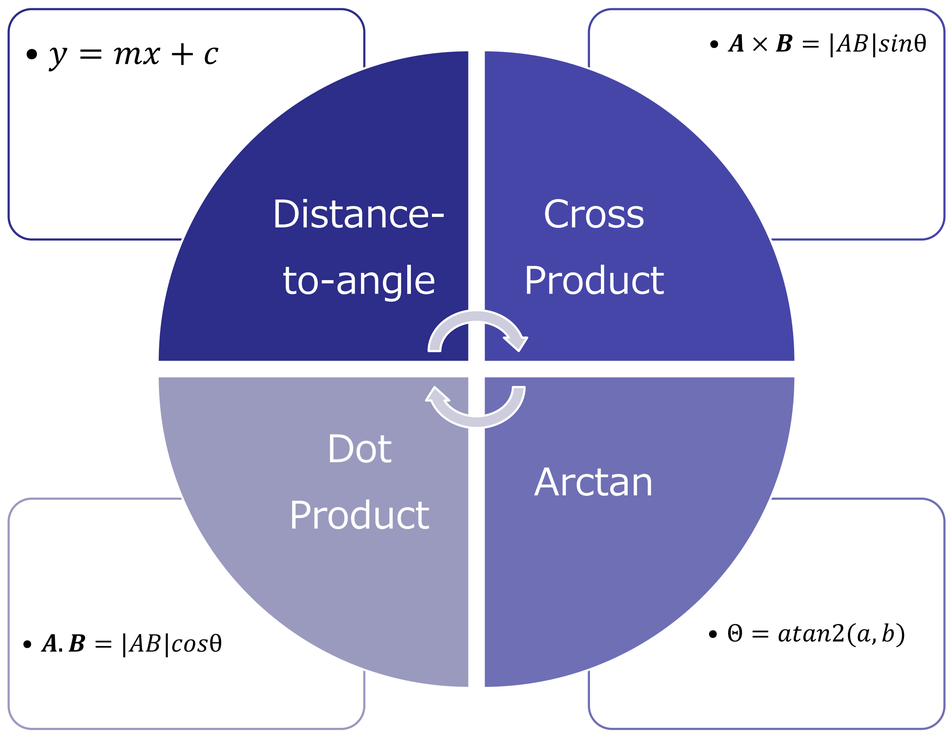
Question:
- **Can we achieve effective hand control with just a standard RGB camera and clever angle measurement?**

Proposal:
- **We explore simple, fast, and accurate ways to measure hand joint angles using a single RGB camera.**



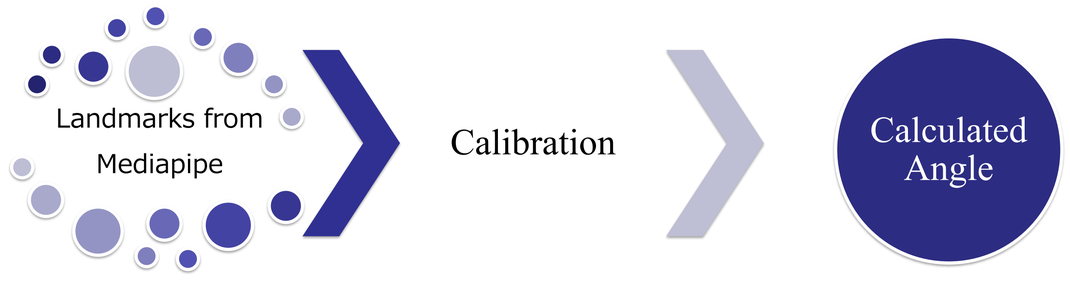
Distance Method Outperforms Trigonometric Approaches

Proposed Methodology



Mediapipe outputs pseudo 3D coordinates of different points in hand, called landmarks. These 3D vectors are then used to calculate angle between tip of each fingers and the wrist using four methods.

Distance-to-Angle Method



Pseudo 3D Vector Coordinates

Maximum and minimum distance for open and closed hand(Euclidean)

Angle = m * Distance + c *Linear Interpolation - m, c from Calibration*

Results

	MAE	R^2	Pearson Correlation
Cosine(dot)	29.64	0.79	0.96
Cross Product	29.64	0.79	0.96
Arctan	23.22	0.83	0.94
Distance to angle	**1.77**	**.99**	**.998**

Table 1: Performance Matrices

*MAE= Mean absolute error

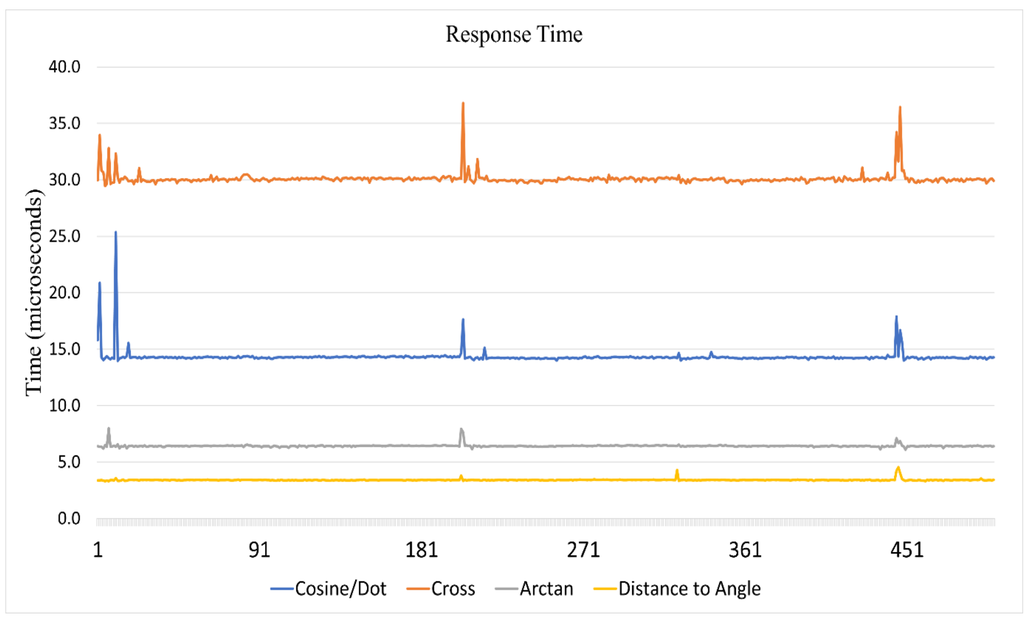


Figure 1: Response Time across datapoints

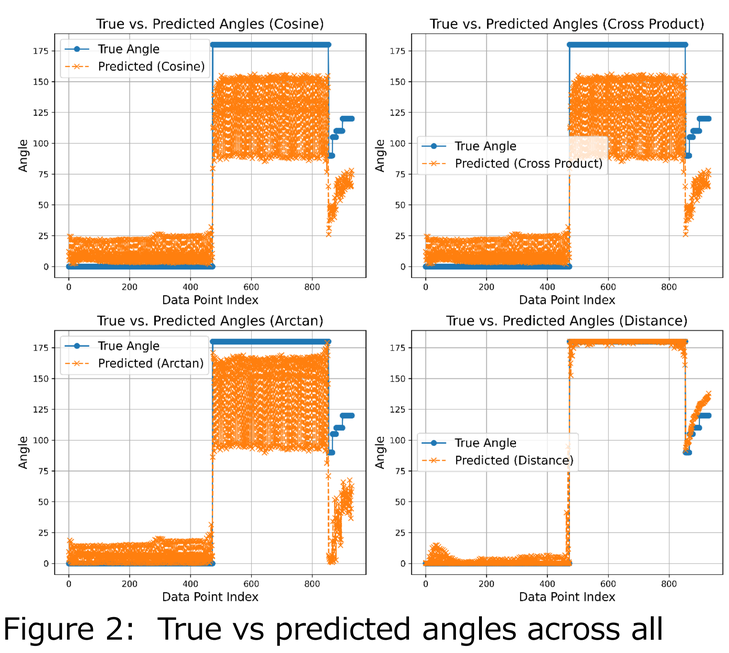


Figure 2: True vs predicted angles across all data points for each method

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MobDenseNet: A Hybrid Deep Learning Model for Brain Tumor Classification Using MRI

Meher Afroj and Dr. Md. Rubaiyat Hossain Mondal

Abstract

This study presents a hybrid DL model MobDenseNet, using the concept of MobileNetV1 and DenseNet121 with feature fusion ensemble and fine-tuning to classify brain tumors using MRI images. MobDenseNet outperforms existing models to distinguish between glioma, meningioma, pituitary, and healthy brain tumors, gaining **98.4%** and **96.02%** accuracy on two benchmark datasets. To assess model's effectiveness on diverse, unseen data, cross-dataset evaluations are conducted, using subset of two additional dataset from different domain.

Background

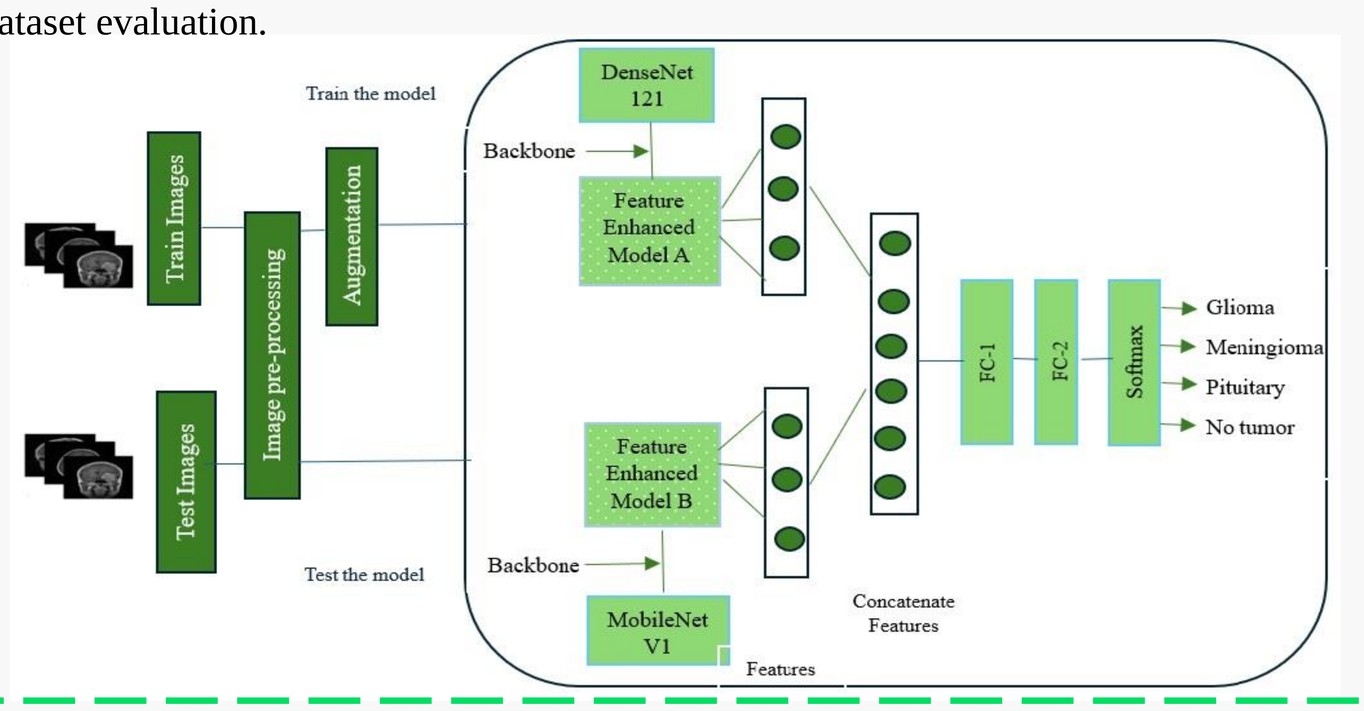
- Gopal et al. [2023] proposed a hybrid ensemble model using five pretrained models on different datasets. And tested on three multiclass datasets with average accuracy of 97.2%.
- Sandhiya et al. [2024] fused features from InceptionV3 and DenseNet201 and classify multiclass MRI images using PSO-KELM, gained accuracy of 98.2%.
- Shahriar et al [2024] proposed an ensemble model named IVX16 that gained the accuracy of 96.9% on 3264 MRI images of four classes.

Research Gap

Although deep hybrid models has shown promising results in . Different hybrid models improve performance and have been tested on multiple datasets. But These model's generalizability still be unexplored through cross-dataset evaluation.

Proposed Architecture with Contribution

The workflow of MobDenseNet is illustrated in figure, where DenseNet121 and MobileNetV1 serve as backbones for feature extraction (Models A and B). Extracted features are fused, passed through fully connected layers, and classified into tumor types enabling the model to evaluated on two benchmark datasets and validated through cross-dataset evaluation.



Class Distribution in the Datasets

Dataset	Glioma Class 0	Meningioma Class1	Pituitary Class 2	No-tumor Class 4	Total
Dataset1 [Figshare]	1426	930	708	-----	3064
Dataset2 [SartajBuvaji]	926	937	901	500	3264
Dataset3 [Br35]	300	300	300	-----	900
Dataset4 [Crystal brain MRIs]	302	302	302	-----	906

Results on Two Benchmark Datasets

- MobDenseNet achieved accuracy of 98.4% on Dataset1 and 96.02% on Dataset2 that surpasses other models.

	MobilenetV1	Xception	DenseNet121	InceptionV3	VGG19	MobDenseNet
Accuracy on Dataset1	0.928	0.908	0.902	0.941	0.876	0.984
Accuracy on Dataset2	0.938	0.889	0.917	0.918	0.828	0.960

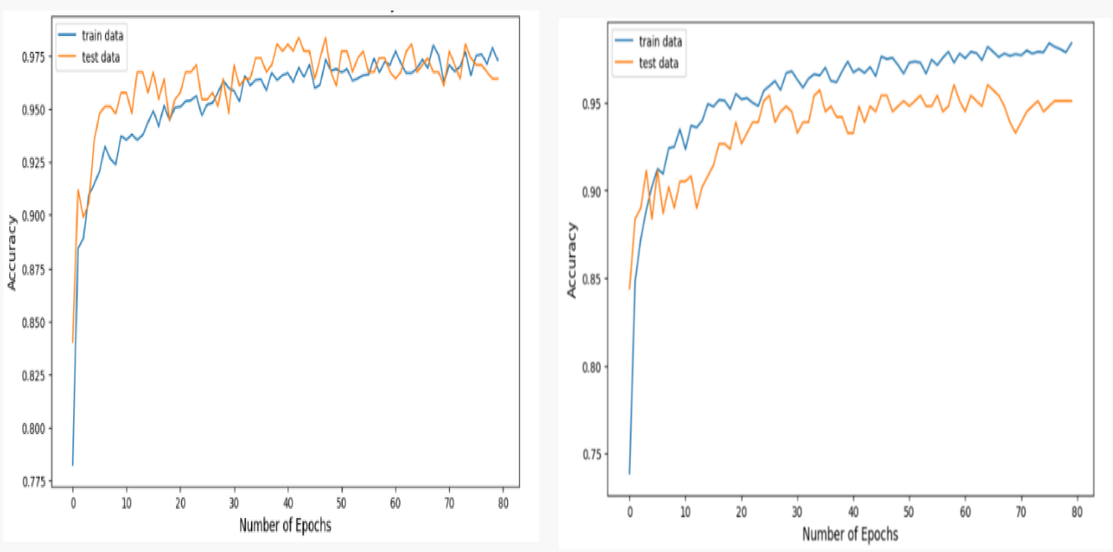


Figure: Accuracy curve on Dataset1 (left) and on Dataset2 (right)

Results on Cross-dataset evaluation

- Images of Dataset-1 is used to train the model and Images from three different databases are used to test the model individually.
- Train Test accuracy of MobDenseNet is compared with underlying backbone models.
- Accuracy result indicates superiority of the proposed model on cross-dataset investigation.

Train		Test		Accuracy					
Database	Images	Database	Images	MobDenseNet		DenseNet121		MobileNetV1	
				Train	Test	Train	Test	Train	Test
Figshare	3064	Sartaj	540	97.9%	91.3%	92.3%	87%	92.8%	88.2%
		Br35	906	98.1%	91.8%	93.2%	88%	93.7%	89.7%
		Crystal MRI	900	97.7%	91.5%	92.8%	84%	93.2%	85.6%

Conclusion

Cross-dataset evaluation enhances model robustness and trustworthiness in health informatics. Performance of MobDenseNet is evaluated across datasets, with future improvements focusing on larger datasets for better accuracy in brain tumor identification.

A Deep Learning-based Efficient Approach for High Quality Image Restoration

Md. Raihan Mahamud and Md. Jarez Miah

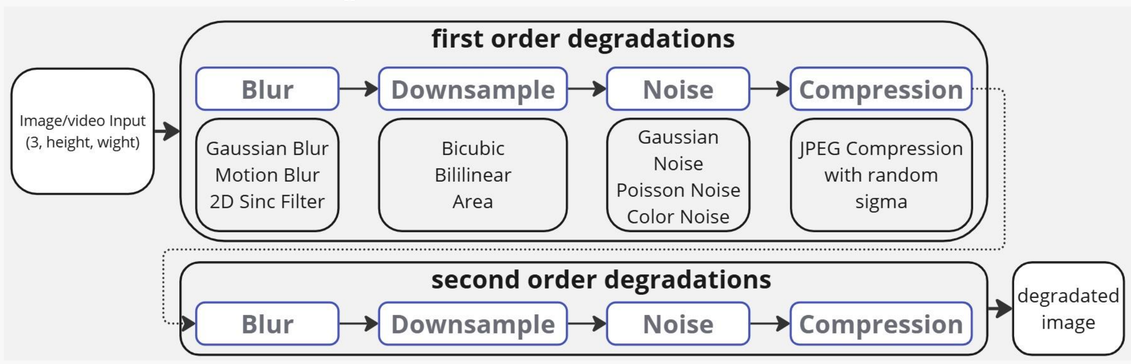
Abstract: This study develops an advanced super-resolution (SR) model for high quality image restoration from noisy images, addressing complex degradations such as noise, blur, and compression artifacts. Using peak signal-to-noise ratio (PSNR)-guided restoration, the model achieves state-of-the-art performance in perceptual quality, controllable restoration and computational efficiency.

Background:

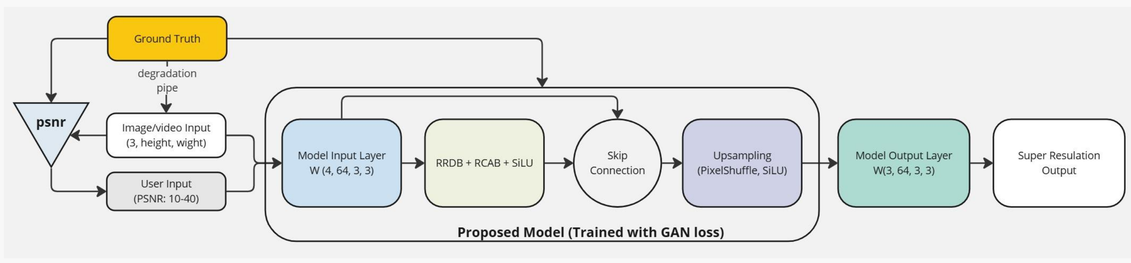
- High quality images are essential for accurate diagnosis, surveillance, scientific research, and environment monitoring etc.
- Mobile photography is often compromised by limited sensor capacity and small apertures [1].
- Satellite imagery suffers from atmospheric interference, motion blur, variable lighting, etc.
- Existing SR models face significant challenges due to their high computational demands [2].

Objectives:

- To generate degradation close to real world images, multi-order degradation is introduced.



- To develop an efficient network, pixel-shuffle up-sampling, RCABs and E-RRDB blocks are used.

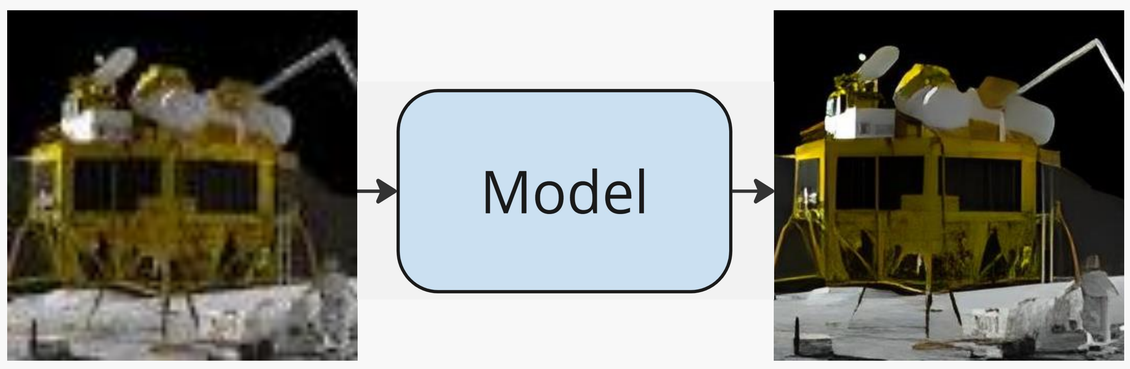


E-RRDB: Enhanced Residual-in-Residual Dense Blocks.
RCAB: Residual Channel Attention Blocks.

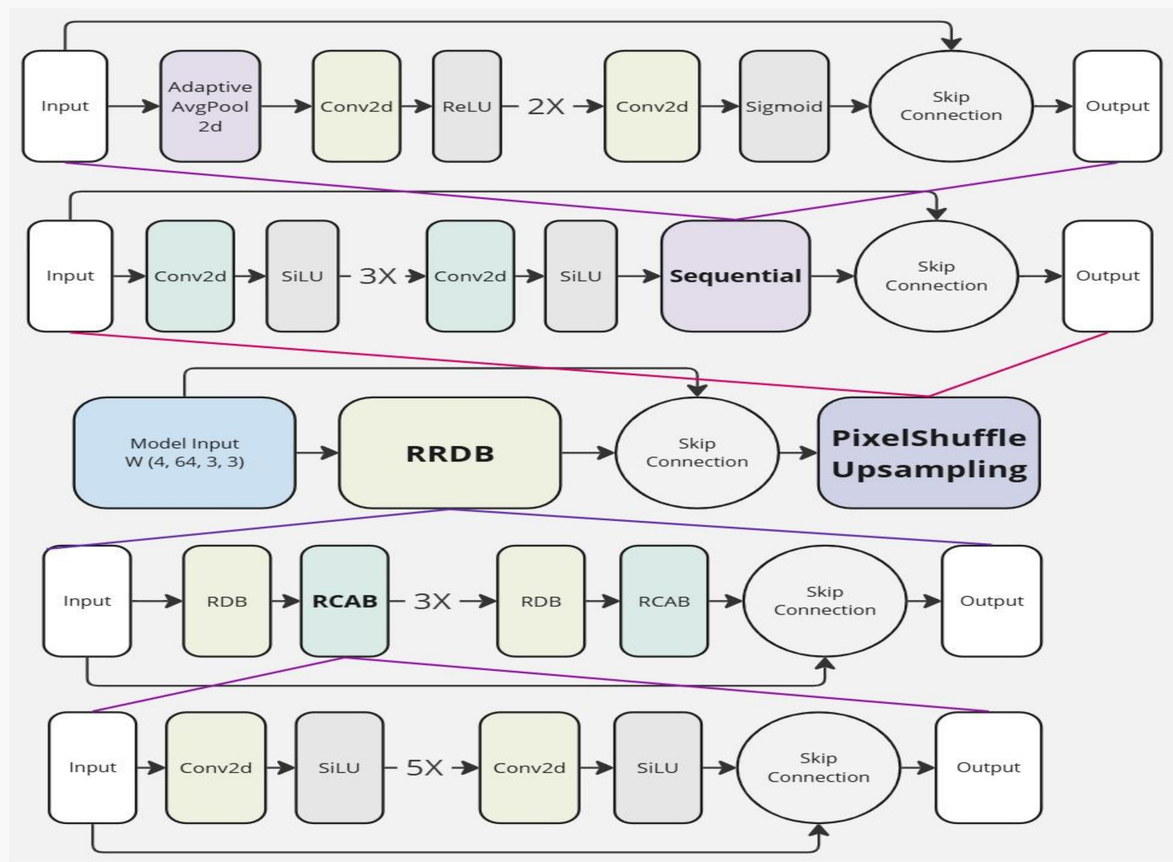
- To make the model lightweight and computationally efficient, bottleneck is used.

Proposed Idea:

Training a deep-learning-based model using degraded image along with degradation level improves the performance of the model.



Methodology:



Contributions:

- Architectural and computational efficiency without compromising model performance.
- Scalable and easily installable for edge devices like CCTV, cell phone, IoT devices, and satellite.
- Superior performance than the existing SR models.

Results:

The proposed SR model outperforms the existing methods.

Model	PSNR (dB)	SSIM	LPIPS	Inference Time (ms)	GPU memory usage (MB)
Bicubic	26.91	0.756	0.360	-	-
SRCNN	30.48	0.840	0.290	25.4	800
VDSR	31.35	0.850	0.260	34.1	1200
ESRGAN	30.62	0.810	0.265	42.7	1600
Real-ESRGAN	31.10	0.858	0.225	45.8	1750
Proposed Model	**31.88**	**0.874**	**0.180**	**29.6**	**960**

SSIM: Structural Similarity Index Measure. **LPIPS:** Learned Perceptual Image Patch Similarity.

References:

[1] A. Ignatov *et al.,* "Dslr-quality photos on mobile devices with deep convolutional networks," *Proceedings of the IEEE international conference on computer vision*, pp. 3277–3285, 2017.

[2] X. Wang *et al.,* "Real-ESRGAN: Training real-world blind super-resolution with pure synthetic data," *Proceedings of the IEEE International Conference on Computer Vision*, pp. 1905-1914, 2021.

SmartList: Collaborative Expense Tracking with Data-Driven Insights

Md. Al Hussain Talukder
Samin Rahman Khan

Abstract

Managing shared expenses in a large household or group is often chaotic—manual tracking leads to disputes, price blindness, and inefficiencies. **SmartList** is an integrated mobile app designed to simplify collaborative expense tracking and list management by combining innovative input methods with data-driven insights.

- **Real-Time Collaboration:** Seamlessly sync shared lists and budgets across users.
- **Smart Inputs:** Use Google Image scanning to extract receipt data and Google Voice for hands-free logging.
- **Predictive Analytics:** Leverage historical price comparisons to forecast expenses and optimize budgeting.

SmartList transforms financial chaos into organized, actionable insights.

Background & Motivation

Real-Life Inspiration:

Living in a 14-person shared space revealed:

- **Chaotic Tracking:** Manual spreadsheets caused disputes/trust issues.
- **Price Uncertainty:** Grocery prices fluctuated daily, but no tool compared historical data to detect overcharges.
- **No Collaboration:** No app synced group budgets transparently.

Broader Need:

These struggles mirror global challenges:

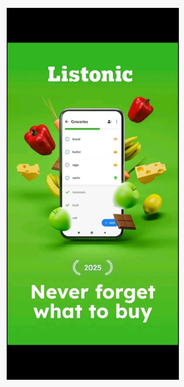
- 73% of shared households face expense conflicts *(2024 FinTech Survey)*.
- 40% abandon tools due to poor UX, wasting ~2hr/week *(App Annie)*.

Existing Solutions & Market Gaps

App	Strengths	Weaknesses
Listonic (10M+)	Shared lists, voice input, recipes	✗ No expense tracking, price analytics
Fordo (Bangla)	Localized UI, quick lists	✗ No group sync, basic insights
Expensify/Wally	Automation, AI-driven analytics	✗ Siloed features, no collaboration

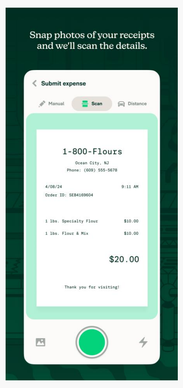
Key Market Gaps:

- **Fragmented Tools**: No app merges lists, expenses, *and* analytics.
- **No Real-Time Collaboration**: Groups lack synced budgets/transparency.
- **Static Data**: Missing price trends or predictive insights.

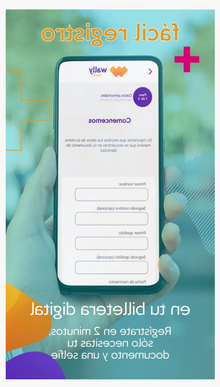


Google Play/ **Listonic**

Google Play/ **Fordo**



Google Play/ **Expensify**



Google Play/ **wally**

Problem Statement & Innovation

Why SmartList?

Existing apps force users to juggle multiple tools, leading to:

- Errors in manual tracking.
- Overspending due to price blindness.
- Frustration from disjointed collaboration.

SmartList Solves This By:

Gap	Innovation
Fragmented Tools	✓ All-in-One Platform: Lists + Expenses + Analytics
No Collaboration	✓ Real-Time Sync: Group budgets with role-based access
Static Data	✓ Smart Insights: Price comparison + Predictive budgets
Localization Limits	✓ Bangla/English UI: Scalable yet region-friendly

Proposed Idea & Methodology

Frontend (React Native)

- **Intuitive UI**: Drag-and-drop lists, Bangla/English toggle.
- **Smart Inputs**:
  - *Image Scanning*: Auto-extract prices from receipts.
  - *Voice Commands*: Hands-free item logging.
- **Real-Time Sync**: Instant group updates.

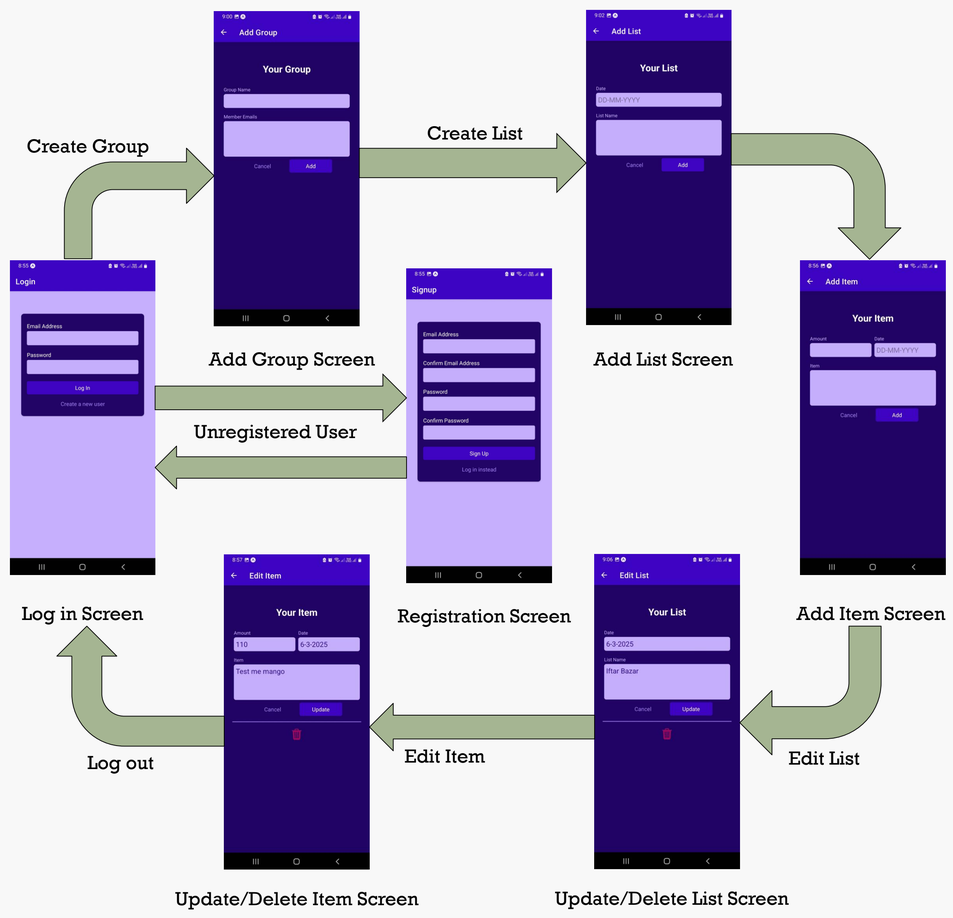
Backend (Spring Boot)

- **APIs**: CRUD, auth, group management.
- **MySQL**: Scalable storage for lists/expenses.

Data Science

- **Price Comparison**: Historical trends + outlier detection.

UX Flows



Work in Progress

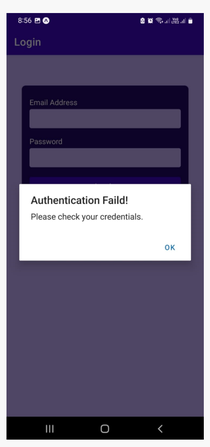
Current Development:

- The project is in its early stage, with the primary focus on developing the UI using React Native.
- Early prototypes are being built to validate user experience and design concepts before full implementation.

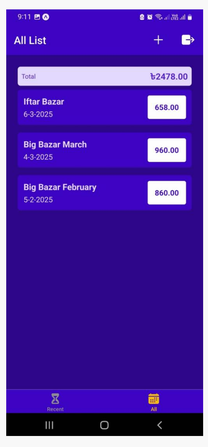
Next Steps & Future Work:

- **Backend Development:** Implementing Java Spring Boot with a MySQL database for secure data storage and management. Real-Time Group Collaboration with WebSockets.
- **Google API Integration:** Incorporating Google Vision API for image-based receipt scanning and Google Speech-to-Text API for voice-based input.

Results

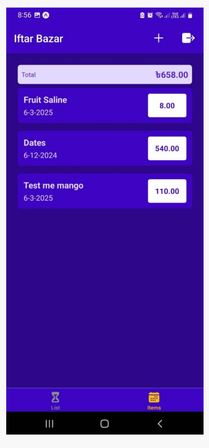


Authentication Screen



All List Screen

Recent List Screen



List Items Screen

Bangla Spam Message Detection using Federated Learning: A Privacy-preserving Model

Mohammad Riyaz Hossen and Hossen A Mustafa

Abstract

This study tackles **Bangla spam detection** using **machine learning** while preserving **privacy** through **federated learning**. Due to **Bangla's unique linguistic traits** and the **scarcity of annotated datasets**, **traditional spam detection methods** are less effective. This research compiles a **Bangla SMS dataset**, analyzes **linguistic patterns**, and employs different **ML classifiers** for SPAM detection. **Federated learning** enables **decentralized model training**, ensuring **user data remains private**. **Experimental results** show that the proposed method achieved an **accuracy of 88.3%, 94.4% precision, 41.8% recall, 57.4% F1-score,** and **39.4% entropy loss**. This work enhances **Bangla spam filtering** and contributes to **privacy-preserving machine learning** in **mobile communications**.

Background & Motivation

The study focuses on privacy-preserving spam detection in Bangla using **Federated Learning (FL)**, addressing the lack of privacy-aware models in existing Bangla spam detection research.

Key Points:

- **Spam Challenges:** Mobile communication has increased spam messages, raising privacy and security concerns, especially in under-resourced languages like Bangla.
- **Existing Research:** Prior studies have explored **machine learning and linguistic features** for Bangla spam detection, such as RNN-based detection (Mohsin Uddin et al., 2019) and spam email classification (Ruhul Amin et al., 2019), but without privacy-focused approaches.
- **Federated Learning (FL):** FL enables decentralized spam detection while preserving user data privacy. It has been applied to English spam filtering but not to Bangla (M. J. Shanto et al., 2023).
- **Security Techniques:** Methods like **differential privacy** and **secure aggregation** improve FL-based spam detection models.
- **Research Gap:** While FL has been explored for Bangla **word prediction** (Iqramul Haq et al., 2022) (M. Rahman et al.), no **privacy-preserving FL model** exists for Bangla spam detection.

Different approach details in previous spam detection research

Study	Dataset used	Language	Method used	FL used	Evaluation matrices
MohsinUddin et al.[33]	SMS	Bangla	RNN(LSTM,GRU), NB, LR, SVM	No	Accuracy, F1 score
RuhulAmin et al.[1]	Email	Bangla	Naive Bayes,KNN, DecisionTree,AdaBoost,RF	No	Accuracy,Sensitivity
IkramUlHaq et al.[34]	Email	English	NLP, FL	Yes	Accuracy
JavedAhmed et al.[27]	SMS	English	Deep learning, LSTM	Yes	Accuracy, Recall,F1
XinJin et al.[13]	Images	English	Clustering	No	detection accuracy
Harshal et al.[17]	OSN posts, comments, reviews	English	Preprocessing and machine learning classifier algorithms.	No	Accuracy, Precision, Recall, F1 score
Milivoje et al.[21]	SMS	English	CNN, ML	No	Accuracy, F1 Score
Saeedreza et al.[29]	Net-spam	English	Graph based	No	Accuracy, Sensitivity
MeetRajdev et al.[23]	tweets	English	flat classifier	No	Accuracy
AnkitKumar et al.[11]	Cyberbullies	English	Traditional probability	No	Security and privacy
FdezRiverola et al.[5]	Email	English	Lazy learning	No	Spam hunt percentage

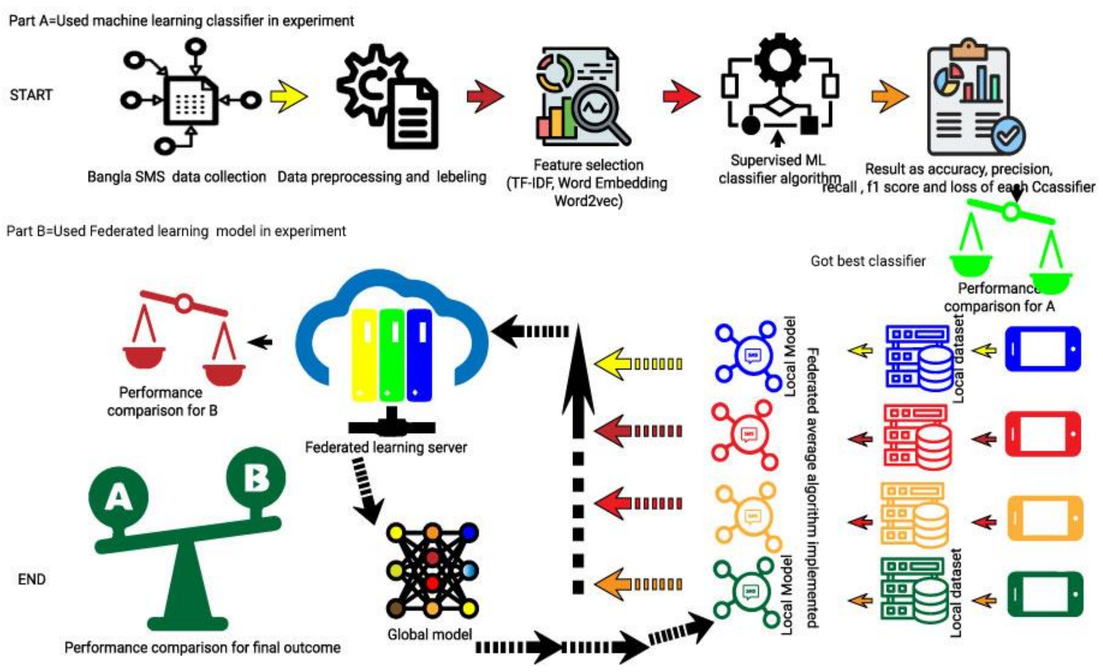
Objective: The study aims to **bridge this gap** by developing a privacy-preserving **FL-based Bangla spam detection model**.

Proposed Idea and Methodology

The research focuses on developing a **federated learning-based Bangla SMS spam detection model** to improve privacy and security.

Key Points:

- **Data Collection:** A Bangla SMS dataset will be gathered via a **mobile app**, where users will label messages as **spam or not**.
- **Preprocessing & Classification:** Various **machine learning classifiers** (Naïve Bayes, Random Forest, SVM) will be tested after preprocessing.
- **Federated Learning (FL):** The model will use **FL**, simulating mobile devices as clients to ensure **decentralized training** and **user data privacy**.
- **Privacy Techniques: Differential privacy** and **secure aggregation** will be implemented to enhance security.
- **Performance Evaluation:** The model's accuracy, precision, recall, and **F1-score** will be assessed and compared with **traditional classifiers** and **existing methods**. Figure I illustrates all of the above description.



Results

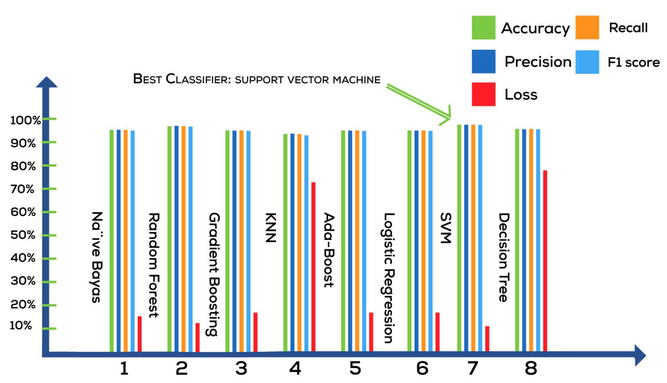


Figure: Results of Traditional Machine Learning Classifiers

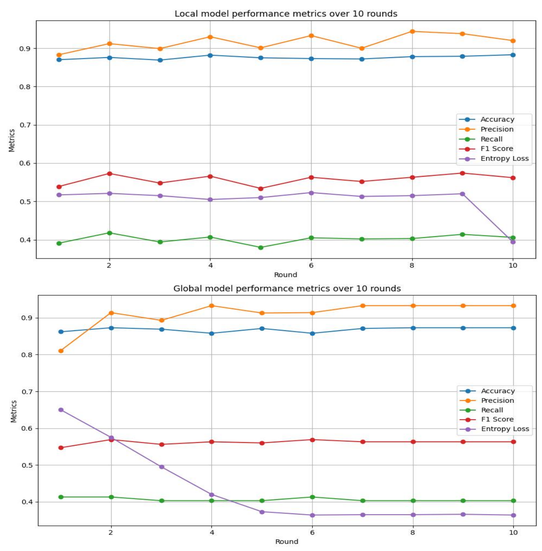


Figure: Results of Local and Global Models in Federated Learning

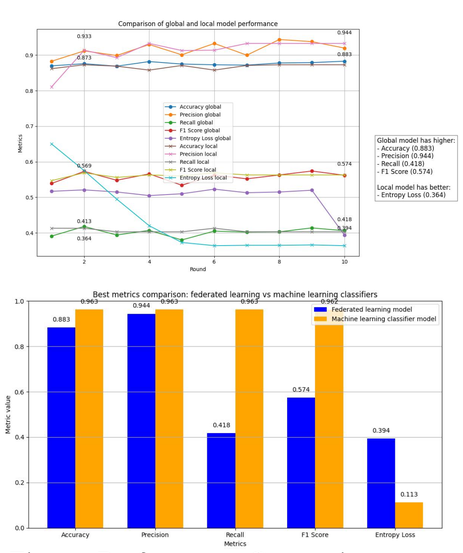


Figure: Performance Comparison

Result Analysis :
Federated learning provides enhanced data privacy while slightly reducing spam detection performance compared to traditional methods.

A Comparative Analysis of Deep Learning and Machine Learning Approaches for Phylogenetic Model Selection

Samuel Rahman Auvro and Prottoy Saha

Abstract

The accuracy of Phylogenetic model reconstruction hinges on appropriate model selection, yet traditional methods are often computationally expensive. This study compares deep learning (DL) and machine learning (ML) approaches, specifically ModelRevelator and ModelTeller, for phylogenetic model selection. ModelRevelator employs two deep neural networks, predicting sequence evolution models and rate heterogeneity without tree reconstruction, making it the fastest method. In contrast, ModelTeller uses Random Forest regression on sequence alignment features and is particularly effective for branch-length estimation. While both methods outperform traditional approaches like AIC and BIC in terms of accuracy and efficiency, the choice between them depends on the specific research needs, such as dataset size and the importance of branch-length precision.

Background & Motivation

Phylogenetic model selection plays a crucial role in reconstructing evolutionary relationships, directly impacting the accuracy of inferred trees. Traditional likelihood-based methods, such as ModelFinder, rely on statistical criteria like AIC and BIC to compare models. While these methods are effective, they are computationally expensive, making them less practical for large phylogenomic datasets. As the scale of molecular data continues to grow, faster and more efficient alternatives are needed to overcome these computational challenges.

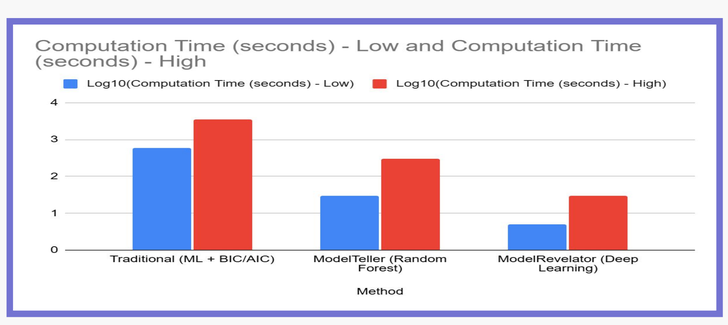


Fig-1: Bar chart comparing Computation-Time

Machine learning (ML) and deep learning (DL) offer promising solutions. ML methods, like ModelTeller, use statistical features, while DL approaches, such as ModelRevelator, employ neural networks to infer models without tree reconstruction. This study compares these techniques, evaluating their efficiency and accuracy in phylogenetics.

Feature	ModelRevelator (Deep Learning)	ModelTeller (Random Forest)
Model Type	Deep Neural Network	Random Forest
Focus Area	General Model Selection	Branch-Length Optimization
Speed	Fastest	Faster than traditional, slower than ModelRevelator
Accuracy	High	Best for branch-length estimation
Training Data	Simulated alignments	Empirical + simulated alignments

Table-1: Feature availability of ModelRevelator & ModelTeller

Proposed Idea and Methodology

ModelRevelator employs two deep neural networks, NNmodelfind and NNalphafind. NNmodelfind predicts one of six sequence evolution models, while NNalphafind determines whether to include a γ-distributed rate heterogeneity component and estimates its shape parameter. This approach eliminates the need for tree reconstruction, making it significantly faster than traditional methods. On the other hand, ModelTeller uses a Random Forest regression model trained on 54 extracted features from sequence alignments. Instead of focusing on general model selection, it optimizes branch-length estimation, which is particularly useful for improving phylogenetic accuracy. While ModelTeller is more computationally efficient than ML-based methods, it is still slower than ModelRevelator due to the additional feature extraction step.

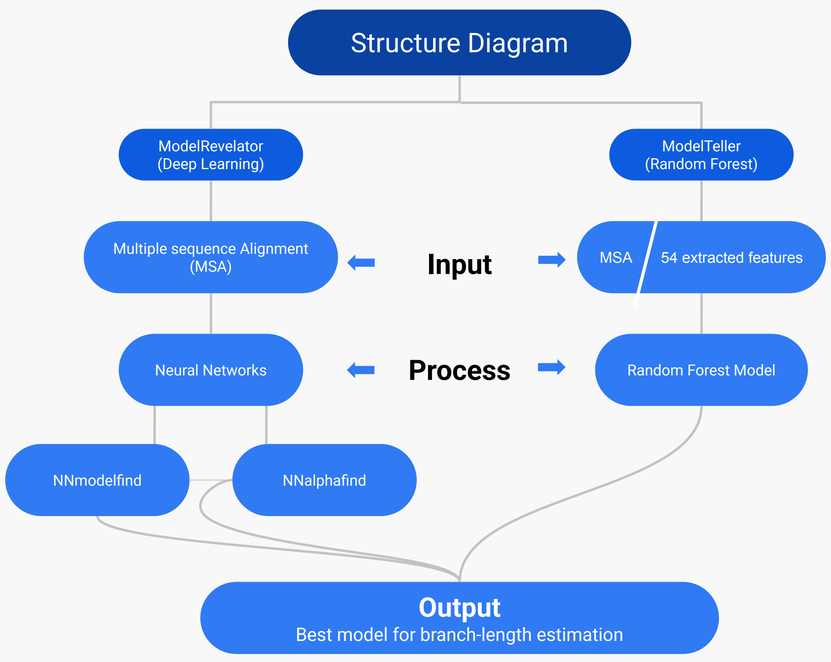


Fig-2: Structure diagram Comparison between two methods.

Results

In terms of speed, ModelRevelator is the fastest method because it predicts the best model without computing likelihoods. ModelTeller, while still much faster than traditional methods, requires additional computational steps for feature extraction. Regarding accuracy, ModelRevelator performs well in general model selection, whereas ModelTeller excels in branch-length estimation. Both methods outperform traditional approaches such as BIC and AIC. The best use cases for each method depend on the research requirements. ModelRevelator is ideal when rapid model selection is needed for large datasets, while ModelTeller is preferable when precise branch-length estimation is critical for accurate tree reconstruction. Overall, both methods offer significant improvements over conventional techniques.

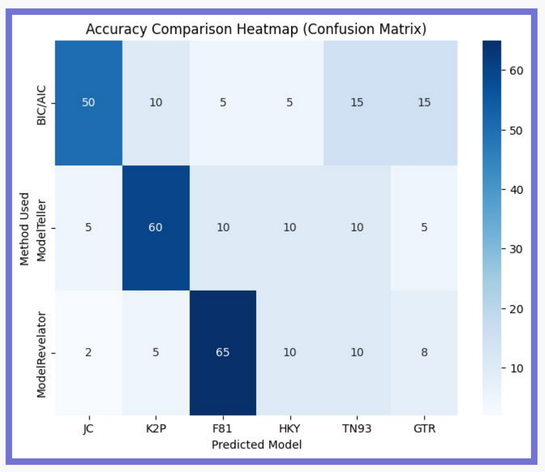


Fig-3: Accuracy comparison Heatmap

Deep Learning Based Demand Forecasting Using Dual-Temporal Characteristics of Booking Data in the Airline Industry

A S M NAZRUL ISLAM, Professor Dr. Md. Liakot Ali

Abstract

In the competitive airline industry, accurate demand forecasting is pivotal for efficient resource allocation and revenue maximization. Traditional forecasting methods often fail to capture complex temporal dependencies in booking data. This paper presents a novel approach using Deep Learning to forecast passenger demand by leveraging dual-temporal characteristics — short-term booking patterns and long-term seasonality trends. By analyzing airline booking datasets, this study demonstrates how Long Short-Term Memory (LSTM) networks effectively model these characteristics, outperforming traditional methods. The proposed framework is evaluated using booking and passenger load factor (PLF) data from a Bangladeshi airline, showcasing its practical applications and potential to enhance decision-making in dynamic pricing and fleet management.

Background & Motivation

- ❑ Airline demand forecasting remains a persistent challenge due to the unpredictable nature of bookings and external market influences.
- ❑ Traditional statistical models (e.g., ARIMA, SARIMA) rely on historical trends but struggle with sudden demand shifts.
- ❑ Existing ML models primarily focus on either short-term demand variations or long-term seasonality but fail to capture their combined influence effectively.
- ❑ Understanding how short-term booking surges interact with long-term demand cycles can provide actionable insights for revenue management, reducing capacity shortages or overestimations.

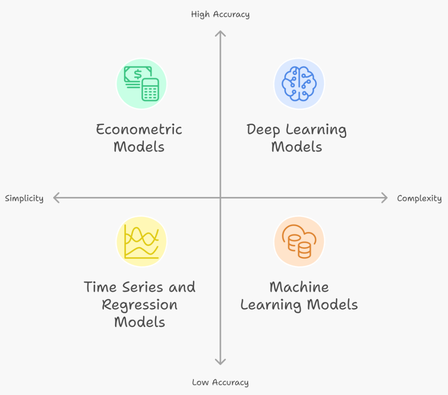


Figure 1. Evolution of air travel demand forecasting methods

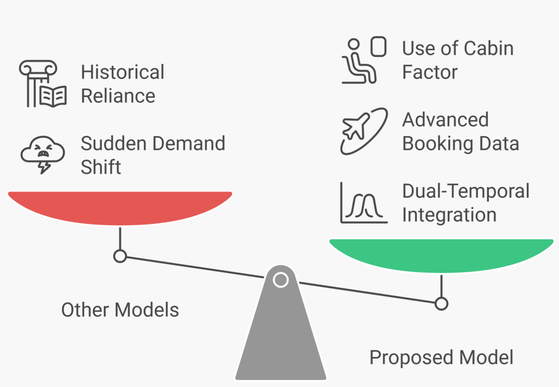


Figure 2. Novelty of the proposed model

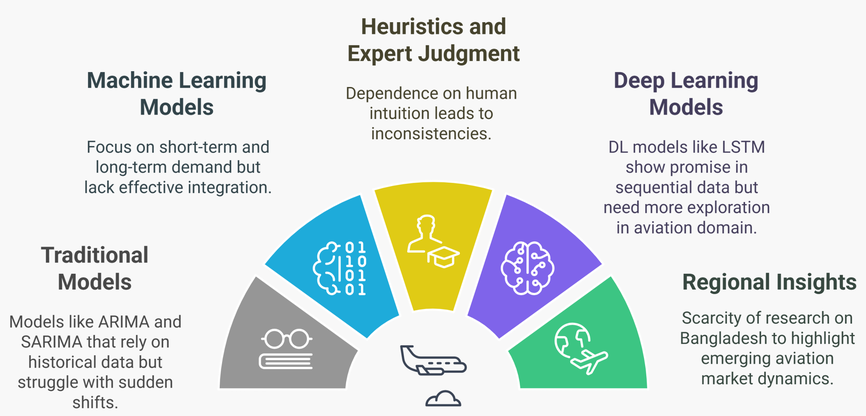


Figure 3. Motivation of the proposed model

Proposed Idea and Methodology

The proposed methodology comprises following steps:

- ❑ Preparation of a comprehensive time series dataset by collecting data from sources like aircraft scheduling, passenger reservation, etc.
- ❑ Performing data cleaning and feature engineering on the prepared dataset to determine suitable and applicable features that have close relationship and impact on the output.
- ❑ Splitting of the cleaned and pre-processed dataset into train, validation and test datasets.
- ❑ Development of a Deep learning-based LSTM model and training it with the train datasets.
- ❑ Fine-tuning of different parameters of the model to increase its performance on the validation datasets.
- ❑ Testing of the model and comparison against other state-of-the-art models.

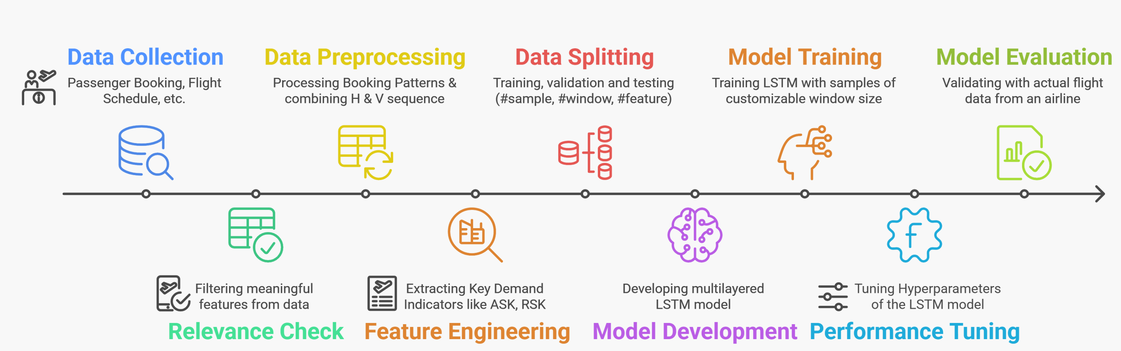


Figure 4. Architectural components of the proposed deep learning model

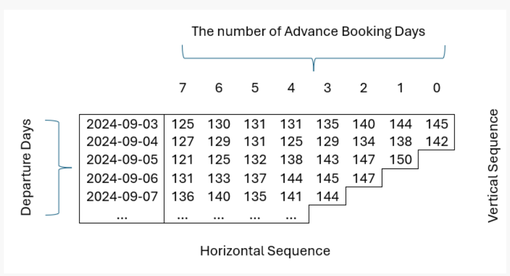


Figure 5. Duel-temporal characteristics of booking data

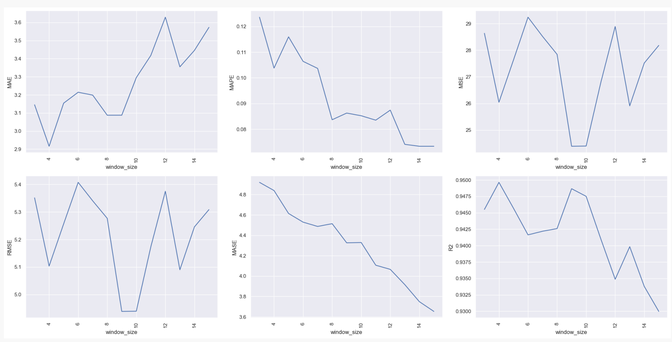


Figure 6. Window size based on relevant metrics

Results

- ❑ Consideration of cabin factor instead of booking count enabled the model to encompass real life scenarios like aircraft change i.e., change in seating capacity.
- ❑ The proposed model attained a good understanding of data 95% along with good MAE, MAPE and RMSE value.
- ❑ Works for any category of flight; be it domestic or international.

Hyperparameter	Value
Learning rate	0.001
Batch size	32
Epoch	50
Number of Layers	4
Number of neurons	64, 32, 16, 1
Probability of dropout	0.2
Activation function	relu
Optimizer	Adam

Figure 7. Hyperparameters of the LSTM model

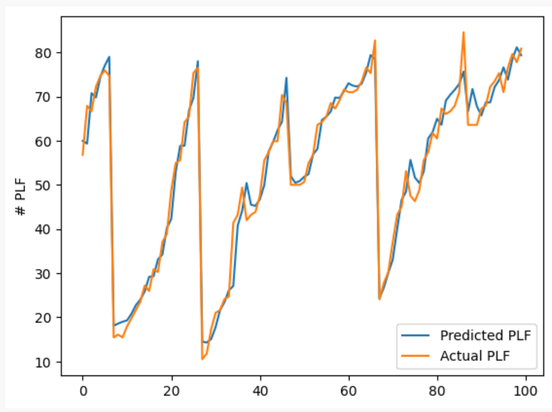


Figure 8. Actual vs Prediction

Metrics	H.He et al.	Proposed
MAE	60.88	3.03
MAPE	4.6	0.08
RMSE	95.55	4.83
R2	-	0.95

Figure 9. Comparison with other study

An Efficient CNN-Based Regression Model for Gaussian Noise Prediction in Color Images

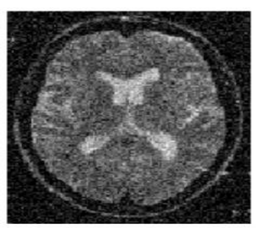
Nasima Islam Bithi and Md. Jarez Miah

Abstract

This study presents a deep learning-based regression model using a custom CNN architecture to predict Gaussian noise levels in RGB images. Trained on Flickr30K, CelebA, and COCO datasets with artificially added noise, the model outperforms existing deep learning (DL) models, including VGG16, ResNet50, MobileNetV2, DenseNet121, ConvNeXt, and AutoencoderKL, as well as the non-DL-based Scikit-learn method. Performance is evaluated using mean absolute error (MAE), mean absolute percentage error (MAPE), root mean squared error (RMSE) and R^2-score metrics. The proposed model demonstrates superior accuracy and generalization, making it a reliable solution for noise estimation in digital imaging applications.

Background & Motivation

- Additive white Gaussian noise (AWGN) is an intensity-independent distortion caused by electronic interference, thermal fluctuations, and sensor imperfections.
- It significantly impacts applications such as medical imaging, autonomous driving, and surveillance.

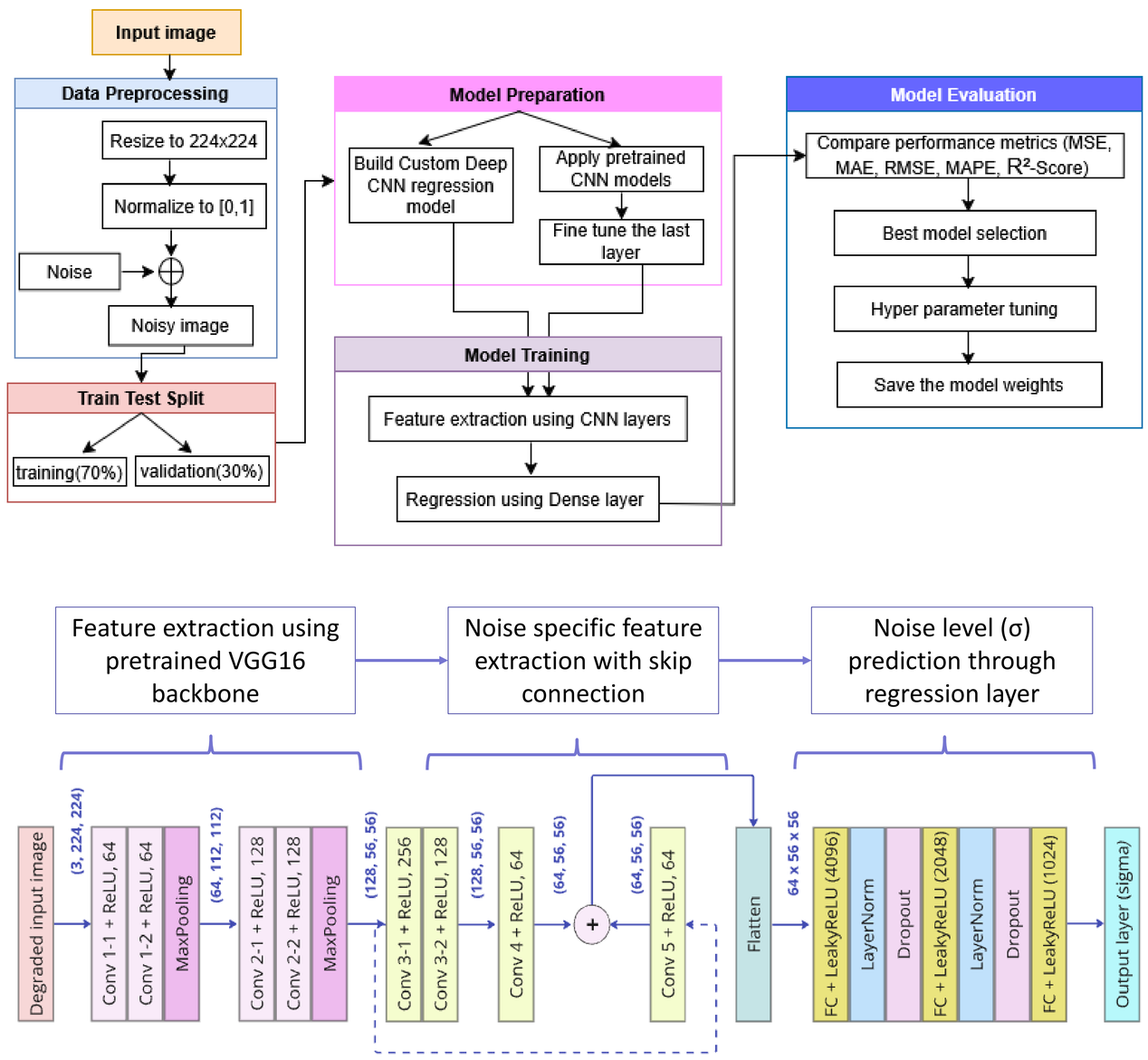


- Accurate noise prediction is essential for effective denoising, segmentation, and super-resolution.
- While existing methods demonstrate high accuracy, they share some common limitations:
  - ✓ DL-based models [1] perform well at low noise levels, but struggle at higher noise levels and in real-life complex scenarios.
  - ✓ Non-DL methods [2] are primarily designed for grayscale images and lack robustness at high noise levels.

Methodology

To simulate real-world degradation, noisy images are generated as:

$$\boldsymbol{I_{noisy\_image}} = \boldsymbol{I_{clean\_image}} + \boldsymbol{AWGN}\ (with\ std.deviation, \sigma)$$



Results

Comparison with DL-based models

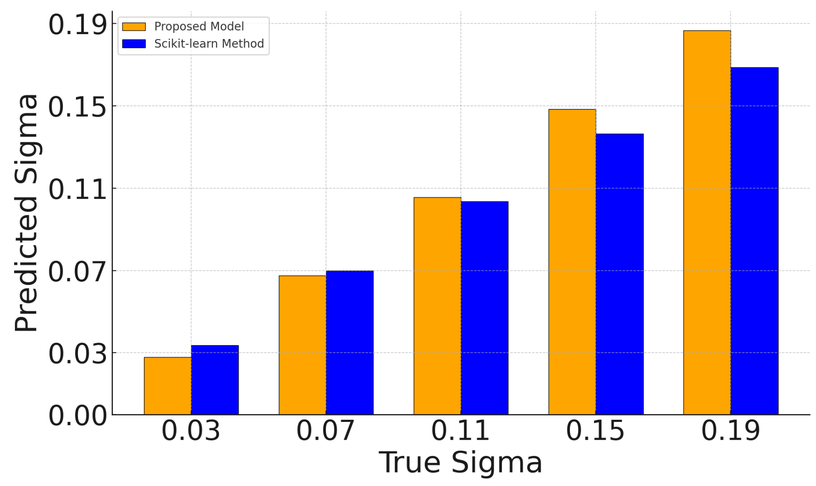
Model	MAE	RMSE	MAPE	R^2-Score
VGG16	0.0193	0.0245	27.9819	0.7966
Resnet50	0.0240	0.0303	39.7463	0.6941
MobilenetV2	0.0147	0.0190	24.4597	0.8795
Densenet121	0.0103	0.0132	16.3313	0.9417
ConvNeXt	0.0171	0.0212	26.5886	0.8492
AutoencoderKL (mode) + custom CNN	0.0114	0.0149	15.4831	0.9246
AutoencoderKL (sample) + custom CNN	0.0124	0.0160	16.9376	0.9145
Proposed model	**0.0038**	**0.0052**	**5.2539**	**0.9910**

True value (σ): **0.1588**
Proposed model (σ): **0.1641**
Scikit-learn method (σ): **0.1406**

Robustness of the proposed model

Dataset	Validation MAE	Validation R^2-score
Flickr30k	0.0038	0.9910
CelebA	**0.0022**	**0.9972**
COCO	0.0030	0.9946

Comparison with wavelet based Scikit-learn method



Reference

[1] A. A. Miranda-González *et al.*, "Denoising Vanilla Autoencoder for RGB and GS Images with Gaussian Noise," *Entropy*, vol. 25, no. 10, p. 1467, 2023.
[2] "Skimage.restoration.estimate_sigma function," *scikit-image documentation*, 2021. [link: https://scikit-image.org/docs/stable/, last accessed on 20 January 2025]

An Efficient IoT-Based Smart Window: A Fresh Air, Light And Temperature Control System

Md. Sohel Rana and Md. Jarez Miah

Abstract

This project develops a smart window system using IoT to enhance indoor comfort and reduce energy waste. The system functions based on the indoor light, temperature conditions, and outside air quality. Sensors measure these factors, and a microcontroller processes the data to control window and blind movements. If the room is dark, blinds open for light; if the room is warm and air quality outside the room is good, the window opens for ventilation. If air quality is poor, the window remains closed. This intelligent system optimizes energy use and ensures a healthy indoor environment. Overall, the proposed system delivers an efficient way to provide a comfortable and healthy indoor environment.

Background & Motivation

- Low light and high temperature condition, poor air quality and inadequate ventilation can cause serious discomfort and affect health.
- Traditional ways for comfortable indoor environments consume excessive energy for lighting and air conditioning.
- IoT-based automated system can reduce energy waste by optimizing resource usage.
- Often IoT applications focus on smart homes, agriculture, and environmental monitoring, but comprehensive smart windows for home remain unexplored.

Objectives

- To build an efficient IoT-based smart window to ensure a comfortable and healthy indoor environment.

Proposed Idea and Methodology

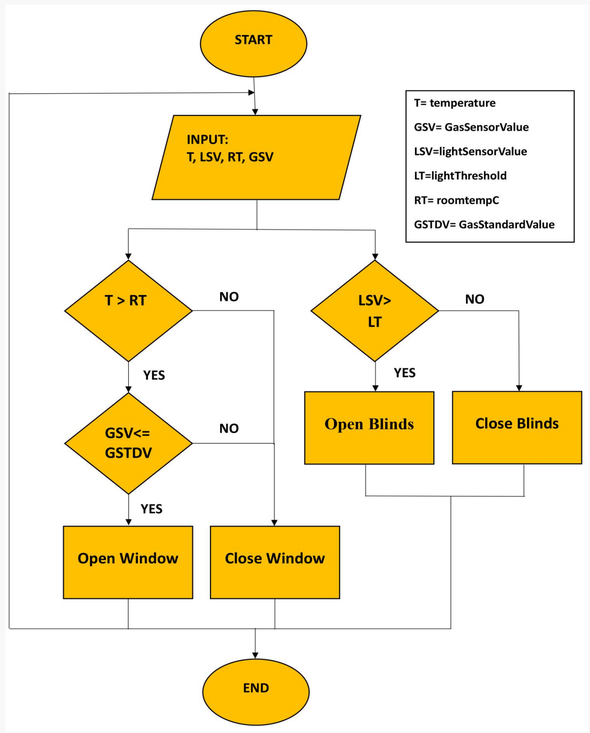


Figure: Flow chart

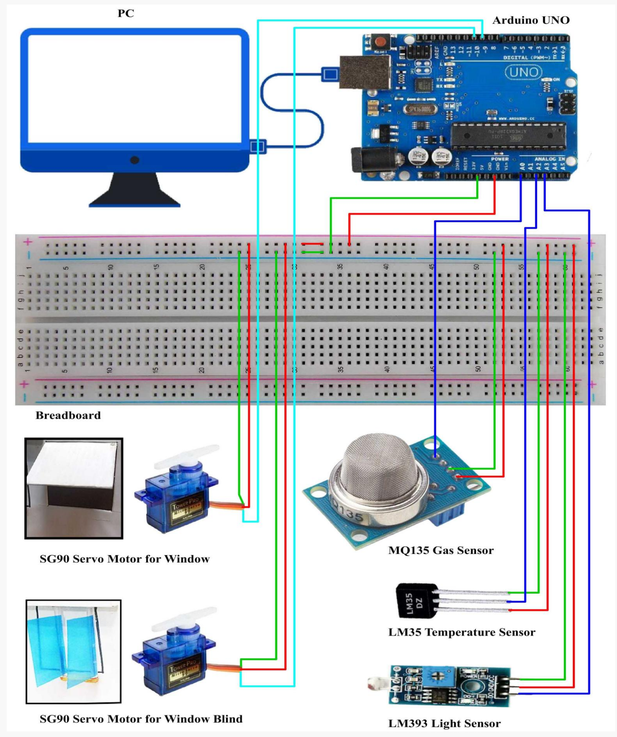


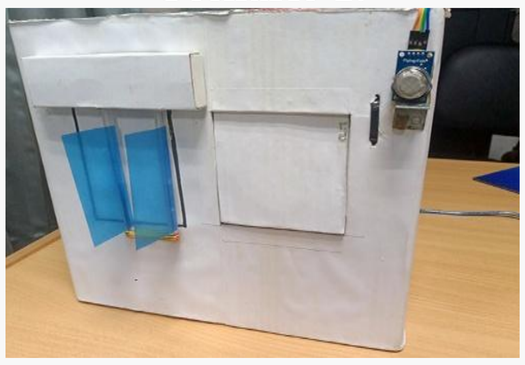
Figure: Circuit diagram

The system functions as follows:

- If the light intensity inside room is low (below a threshold *LT*), the blinds are opened.
- If the temperature exceeds a preset value (*RT*), the microcontroller checks the air quality outside.
- If the outside air quality is good (better than a preset value *GSTDV*), the window is opened to cool down the room.
- The system constantly monitors these conditions, adjusting the blinds and window as needed.

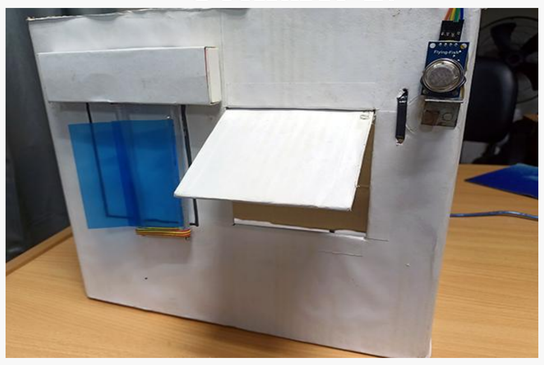
Results

Scenario 1:



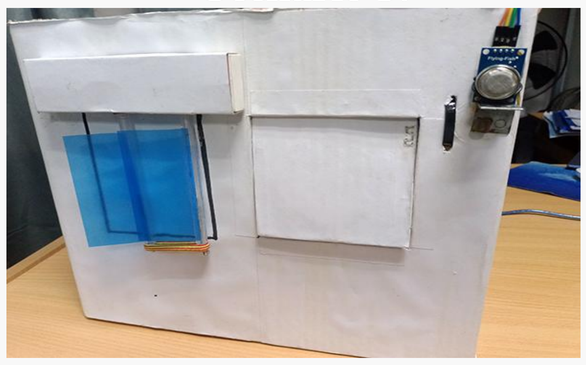
Auto adjustment of blinds in response to inside light conditions.

Scenario 2:



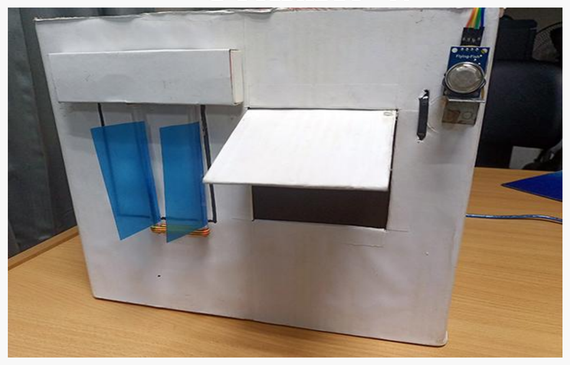
Vertical window in response to high in-room temperature and good outside air quality.

Scenario 3:



System response to low in-room temperature and bad outside air quality.

Scenario 4:



For high in-room temperature, low in-room light level and good outside air quality.

High-Performance PCF-SPR Biosensor Design Using Machine Learning

Mst Rokeya Khatun and Md. Saiful Islam

Abstract: Photonic crystal fiber-based surface plasmon resonance (PCF-SPR) biosensors combine both photonic crystal fiber (PCF) surface plasmon resonance (SPR) techniques to provide very sensitive and ideal optical characteristics. In this study, we have designed a high-sensitivity PCF-SPR biosensor for a refractive index range of 1.31 to 1.42. Additionally, machine learning (ML) regression models were employed to predict the sensor's optical properties to minimize computation time. The biosensor achieved an excellent performance with a maximum wavelength sensitivity of 125,000 nm/RIU, an amplitude sensitivity of -1422.34 RIU^{-1}, a resolution of 8×10^{-7} RIU, and a figure of merit of 2112.15 RIU^{-1}. Among all ML models Extreme Gradient Boosting Regression (XGBR) model performed excellently in predicting the optical parameters. This sensor shows great performance that can be promising for medical and chemical sensing applications.

Background

- PCF-SPR biosensors combine photonic crystal fibers and surface plasmon resonance for high sensitivity and improved optical properties.
- Key design factors like air hole radius, gold layer thickness, and analyte layer thickness influence performance.
- Gold and silver are commonly used materials for SPR applications due to their plasmonic properties.

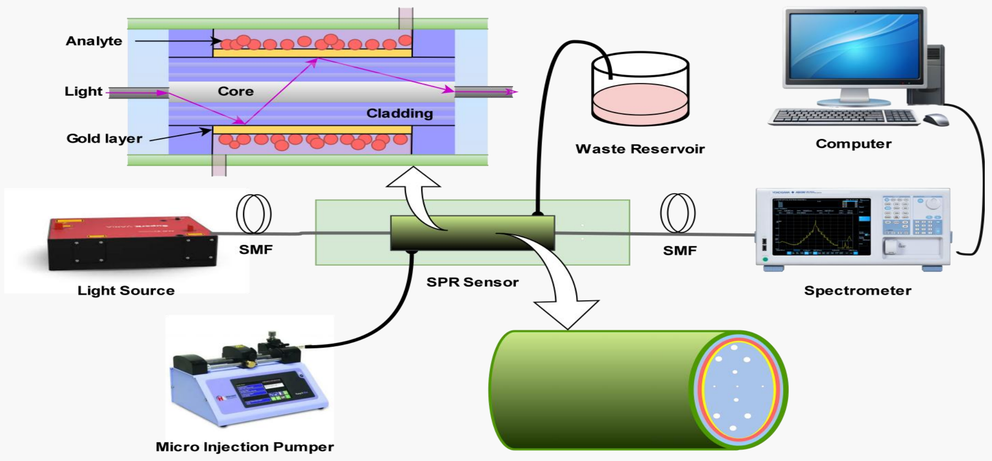


Fig. 1. Schematic diagram of a Fiber-Optic SPR Biosensor system for biochemical detection.

Motivation

- PCF-SPR biosensor optimization faces challenges in balancing sensitivity, accuracy, and signal loss.
- Machine learning (ML) offers a more efficient approach for optimizing sensor performance compared to traditional methods.
- There's a need for more research focused on high-performance, ML-driven PCF-SPR biosensor designs.

Proposed Idea and Methodology

The main objectives of our research is:

-to develop a highly sensitive, efficient PCF-SPR biosensor design with low confinement loss (CL), high amplitude sensitivity (S_A), high wavelength sensitivity (S_λ), low resolution, and high figure of merit (FOM).

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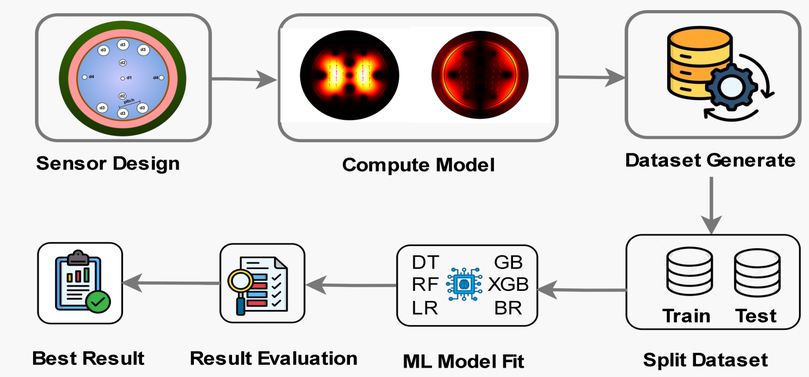
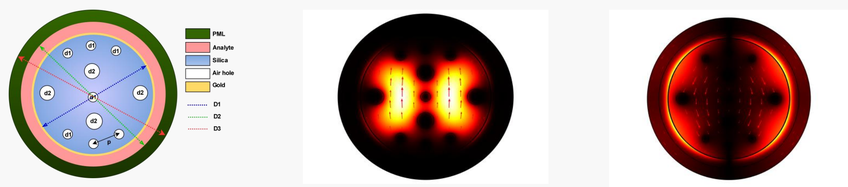


Fig. 2. Research workflow for PCF-SPR biosensor model optimization.



(a) (b) (c)

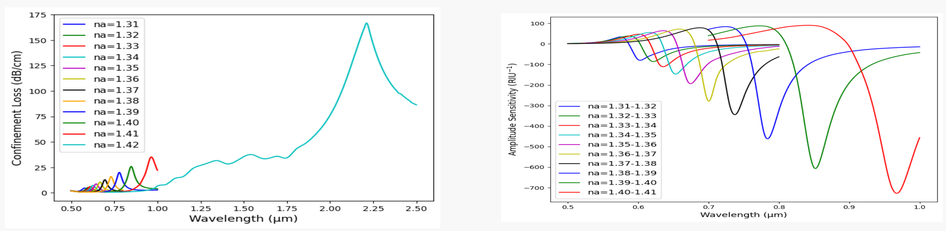
Fig. 3. PCF-SPR biosensor: (a) meshed model, (b) core mode electric field distribution, and (c) SPP mode power flow distribution for y-polarized mode.

The impact of optical parameters on biosensor performance is summarized below.

- Higher FOM → Sharper resonance peak → Improved detection accuracy and resolution
- Higher S_A → Greater intensity variations → More precise signal detection
- Higher S_λ → Larger resonance wavelength shift → Enhanced sensitivity to analyte changes
- Lower CL → Better light propagation → Reduced signal attenuation and improved efficiency

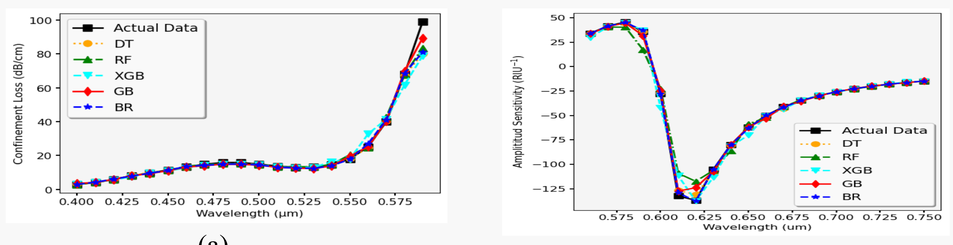
Results

The graphs in Figure show how CL changes with wavelength for different n_a values, with d1 = 0.6 µm, d2 = 1 µm, p = 3 µm, and t_g = 60 nm considered constant. This analysis provides insights into how n_a influences the optical behavior of the sensor. Refractive index (RI) range of 1.31 to 1.42, using gold plasmonic material.



(a) (b)

Fig.4. Change of (a) Confinement loss (b) Amplitude sensitivity with wavelength variation.



(a) (b)

Fig. 5. Validation of (a) confinement loss (b) amplitude sensitivity predictions from various ML models against actual data

ML Models Used: RFR, DTR, GBR, XGBR, KNN, and BR to optimize design, reducing computational cost and time.

XGBR Model Results: Highest predictive accuracy (R^2 = 0.9976, MAE = 0.00221, MSE = 0.00059).

Best Performance Metrics:

S_λ : 125,000 nm/RIU
S_A : -1422.34 RIU^{-1}
Resolution: 8×10^{-7} RIU
FOM: 2112.15 RIU^{-1}

Applications: Suitable for medical diagnostics, disease detection, environmental monitoring, biochemical sensing, and industrial settings.

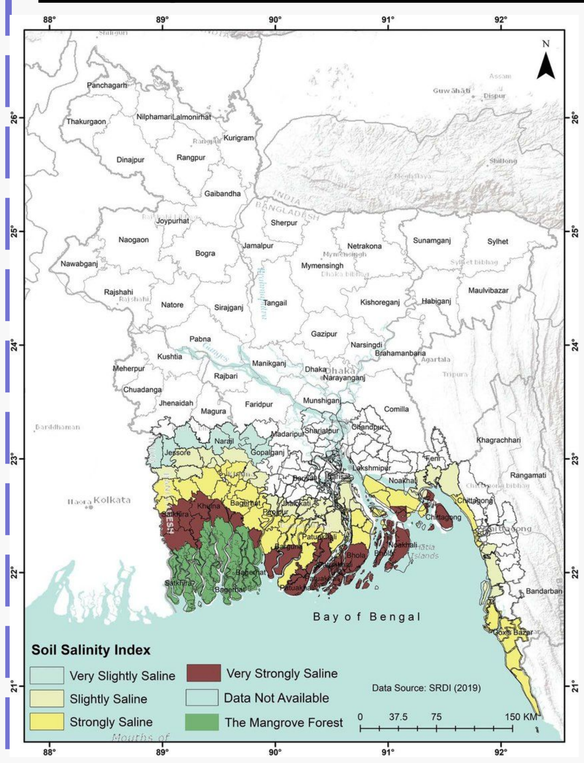
Future Work: Explore other plasmonic materials, enhance ML model generalization, and conduct experimental validations.

A Smart Agriculture System for the Coastal Area of Bangladesh: Leveraging IoT, AI, and Sustainable Practices

Name: Mst Shahnaj Parvin ID: 0424314006

Abstract: Bangladesh's coastal region, which covers over 47,000 square kilometers, is highly vulnerable to the effects of climate change. This region suffers from frequent natural disasters like cyclones, tidal surges, and saline water intrusion which mainly affects land and water. The total amount of salinity affected land in Bangladesh was 83.3 million hectares in 1973, which had been increased up to 102 million hectares in 2000 and the amount has risen to 105.6 million hectares in 2009 and continuing to increase, according to the country's Soil Resources Development Institute (SRDI). In the last 35 years, salinity increased around 26 percent in the country, spreading into non-coastal areas as well[1]. Estimates from the research indicate that Bagerhat, Barguna, Barisal, Bhola, Khulna, Jhalakati, Pirojpur, and Satkhira districts will be affected most adversely. In the coming decades, soil salinity will significantly increase in many areas of Barisal, Chittogram and Khulna districts. It projects a median increase of 26 percent in salinity by 2050, with increases over 55 percent in the most affected areas[2]. Salinity becomes a problem when enough salts accumulate in the root zone to negatively affect plant growth. These challenges have drastically affected agricultural productivity, threatening food security and livelihoods[3]. The need for sustainable agricultural practices that can adapt to changing conditions is paramount. This research proposes the development of a Smart Agriculture System (SAS) tailored for the coastal areas of Bangladesh. This system will leverage emerging technologies like the Internet of Things (IoT), Artificial Intelligence (AI), data analytics and remote sensing to optimize resource use, improve crop resilience, and increase productivity in an environmentally friendly manner[4]. Digital literacy, financial aid, & data security are essential for smart farming[5].

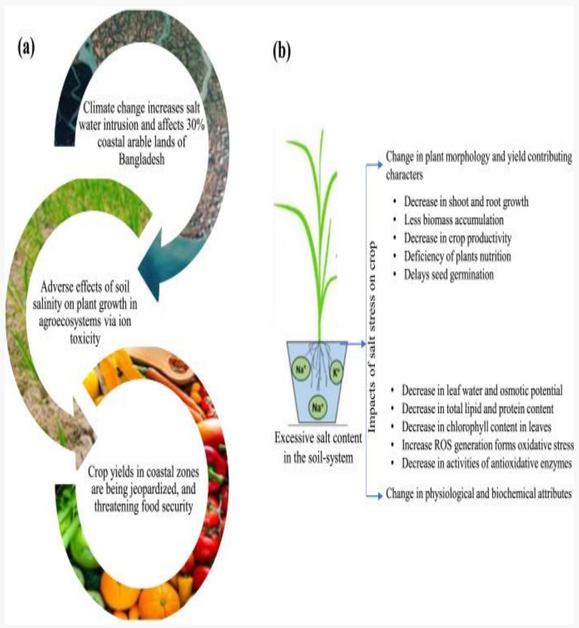
Background & Motivation

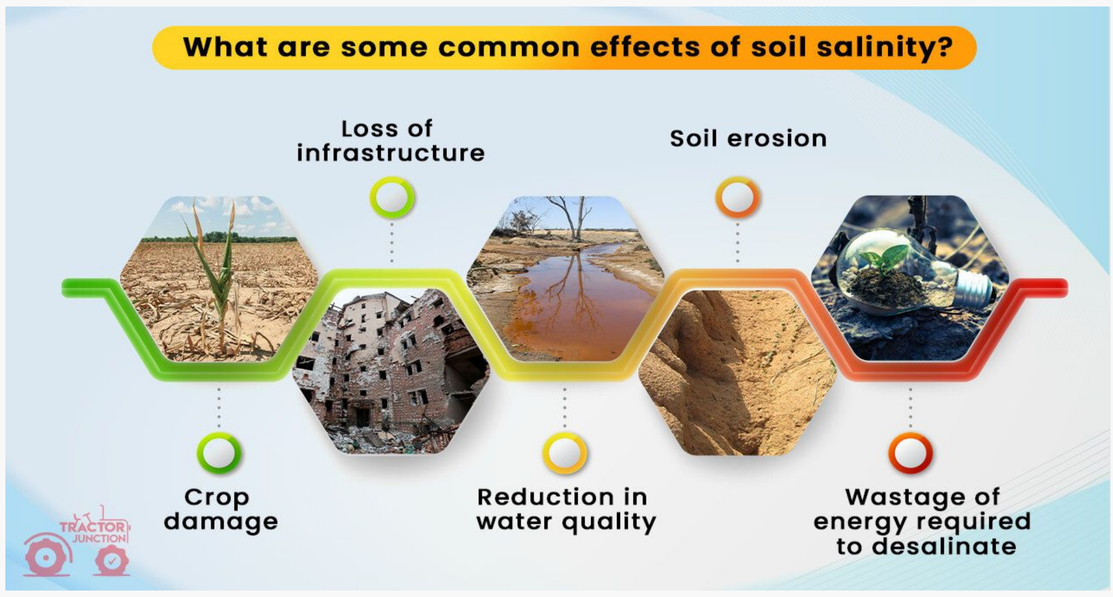


- The total amount of salinity affected land in Bangladesh was 105.6 million hectares in 2009 and continuing to increase (SRDI).
- In the last 35 years, salinity increased around 26 percent in the country, spreading into non-coastal areas as well
- It is projected that by 2050, the salinity will increase over 55 percent in the affected area.

Specific challenges of the coastal regions of Bangladesh:

- Soil Salinity
- Water Scarcity and Flooding
- Climate Change Impact





Proposed Idea and Methodology

Current State and research gap:

It is shown that IoT-based smart agriculture systems have been shown to improve agricultural productivity by offering real-time monitoring and control of critical variables like soil moisture, nutrient levels, and crop health. IoT technology combines sensor systems and web-based software that transfers soil moisture and salinity data to a computer or mobile phone[6].

But high salt levels can affect sensor performance and crop health, making it challenging to maintain optimal growing conditions. While precision or smart agriculture is gradually developing new technologies in farmlands, *more extensive investigations are needed to address the challenges of agricultural digitalization like IoT security, Threat solutions/protocols, Operational technology, Data storage, Cloud platforms, Power supplies.*

Research Objectives:

Primary: To design and implement a smart agriculture system for the coastal areas of Bangladesh.

Specific:

a) To identify the unique agricultural challenges of coastal areas in Bangladesh, including soil salinity, water management, and weather patterns.

b) To develop an IoT-based monitoring system for real-time data collection on soil health, water quality, and crop conditions.

c) To integrate AI-based predictive models for optimizing irrigation, crop selection, and pest control.

d) To assess the effectiveness of the smart agriculture system in improving crop yields, reducing water usage, and mitigating the effects of salinity and extreme weather.

e) To provide recommendations for scaling the system across other coastal regions in Bangladesh.

Methodology:

Phase 1: Needs Assessment and Site Selection
- ★ Conduct a survey to identify key challenges.
- ★ Select pilot locations in different coastal districts for system implementation.

Phase 2: System Design and Development
- ★ IoT Sensor Network
- ★ Data Integration and AI Modeling
- ★ Mobile App Development

Phase 3: Implementation and Testing
- ★ Compare agricultural productivity and resource use before and after the system implementation.
- ★ Evaluate the system's effectiveness in mitigating the effects of salinity, water stress, and climate variability.

Phase 4: Data Analysis and Evaluation
- ★ Deploy the smart agriculture system
- ★ Train local farmers and extension workers
- ★ Monitor key agricultural indicators

Expected Outcomes

- ❏ Improved crop yields through precise monitoring and timely interventions.
- ❏ Efficient use of water resources, reducing the dependency on freshwater in saline environments.
- ❏ Enhanced resilience to climate change through predictive weather and crop models.
- ❏ A scalable smart agriculture framework that can be adapted to other coastal regions.
- ❏ Empowerment of local farmers with real-time information and technology-driven decision-making tools.

Significance of the Research

- ❏ Address the pressing issue of agricultural sustainability in climate-sensitive coastal areas.
- ❏ Contribute to the body of knowledge on the use of IoT and AI in agriculture, especially for regions facing environmental challenges
- ❏ Provide policymakers and agricultural planners with practical solutions that can be implemented at a larger scale.

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Enhancing Workstation Security through System Hardening: A Comprehensive Approach Using CIS Benchmarks

Md. Mamunur Rashid and Prottoy Saha

Abstract

With the growing number of cyber threats, securing IT infrastructure has become a critical concern. Windows OS Hardening is a systematic approach to reducing vulnerabilities, preventing unauthorized access, and enhancing overall system security. This project implements best practices from the Center for Internet Security (CIS) Benchmarks, leveraging security tools and policy enforcement mechanisms to improve workstation protection. The study demonstrates how effective hardening strategies can mitigate threats and establish a secure computing environment.

Background & Motivation

Background

- Windows operating systems are widely used but are often vulnerable due to misconfigurations, outdated software, and weak security settings.
- Cybercriminals exploit these vulnerabilities to launch attacks such as ransomware, unauthorized access, and data breaches.
- Windows OS Hardening ensures enhanced security through strict configurations, regular patching, and advanced threat protection.
- This project aims to strengthen Windows security by utilizing industry standards and security assessment tools.

Motivation

- **Growing Cyber Threats:** Increasing attacks on IT infrastructure demand robust security solutions.
- **Compliance with Standards:** Organizations must adhere to CIS Benchmarks, ISO 27001, and NIST guidelines for security compliance.
- **Addressing System Misconfigurations:** Many security breaches occur due to improper system configurations and the lack of security policies.
- **Automation & Efficiency:** Tools like **CIS-CAT Pro**, PowerShell, and Windows Security Baselines enhance security automation.
- **Optimized Performance:** Hardening techniques not only secure systems but also improve stability and efficiency.

Figure 1: Cyber threat map with red markers showing increasing cyber-attacks around the world.

Figure 2: The illustration of the rising number of security beaches over time.

Proposed Idea & Methodology

This project proposes a structured Windows OS Hardening framework that includes:

CIS Benchmarks & Controls: Implementing industry-standard security guidelines.

User Privilege Management: Enforcing least privilege access to prevent unauthorized system modifications.

Automated Security Audits: Utilizing CIS-CAT Pro and Windows Defender for continuous security assessments.

Network & Firewall Configurations: Restricting unauthorized network access and ensuring robust firewall protection.

System Monitoring & Updates: Automating updates to mitigate security vulnerabilities.

Here is the outline of the methodology:

1. **Initial Security Assessment:** Identifying system vulnerabilities and security gaps.
2. **Implementation of Hardening Techniques:** Applying security policies, enabling encryption, and configuring firewall settings.
3. **Automated Compliance Testing:** Running CIS-CAT Pro and analyzing security reports.
4. **Performance Evaluation:** Measuring the impact of security hardening on system performance.
5. **Reassessment & Continuous Monitoring:** Ensuring long-term security through periodic assessments and policy updates.

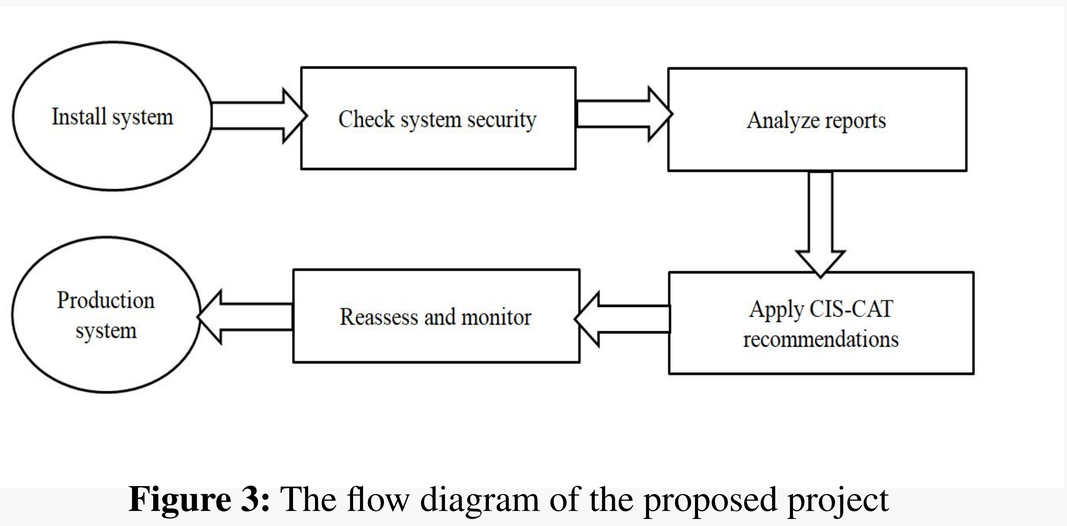


Figure 3: The flow diagram of the proposed project

Results

- **Enhanced System Security:** Reduced attack surfaces and improved security compliance.
- **Minimized Vulnerabilities:** Addressed misconfigurations and enforced strict security controls.
- **Optimized Performance:** Implemented security enhancements without negatively impacting system performance.
- **Improved Compliance:** Successfully aligned system configurations with CIS Benchmarks and industry standards.
- **Compliance Score Improvement:** Security compliance score increased from 60% to 90% (CIS-CAT Assessment).

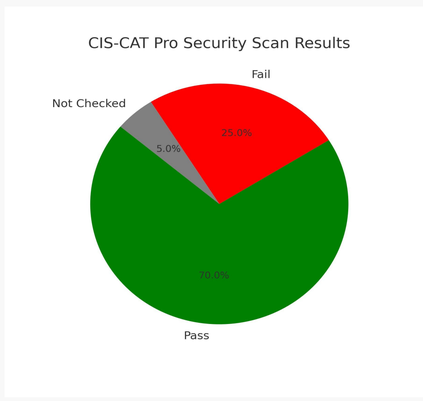


Figure 4: The pie chart representing a sample CIS-CAT Pro security scan report.

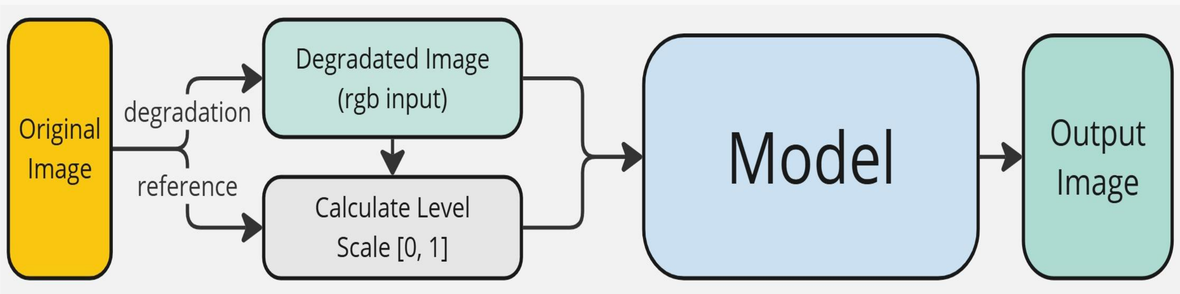
Controllable Image Enhancement Using Deep Network Adaptive Scaling Mechanism

Md. Raihan Mahamud and Md. Jarez Miah

Abstract: Image upscaling is a crucial task in computer vision, enhancing image resolution while preserving details. Traditional Super-Resolution (SR) models typically operate in a blind manner, where users have no control over the degree of enhancements. In this work, we propose a controllable image up-scaling using deep network, which allows users to specify the scaling factor within a continuous range of 0 to 1. The proposed method provides a balance between computational efficiency and flexibility, making it a practical solution for various applications where adaptive image enhancement is required.

Background & Motivation:

- Traditional SR models, including convolutional neural network (CNN) and Transformer-based models, typically perform fixed upscaling (2×, 4×, 8×) and have no control over the output resolution [1].
- They achieve impressive results, but lack flexibility for their blind mechanism and require separate model for different scaling factors [2].
- To address this limitation, we propose a controllable image upscaling approach which allows dynamic scaling factors.



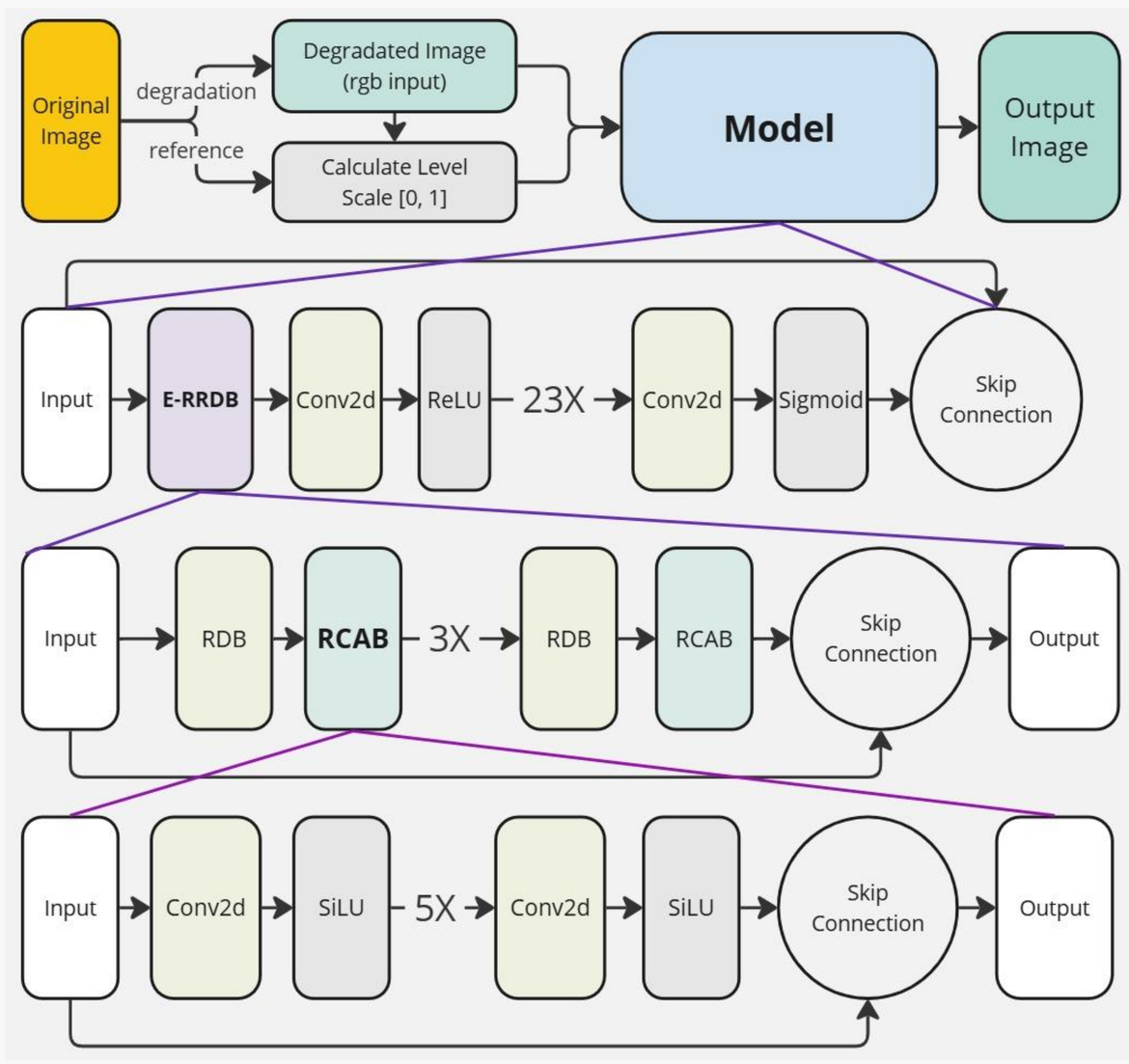
Achievements and Contributions:

- Our method achieves high-quality, flexible image enhancement in different upscaling levels on minimal computational overhead, preserving details.
- A single network to interpolate resolutions, which allows users to control the output by changing the scaling factor continuously from 0.00 to 1.00.

Proposed Idea:

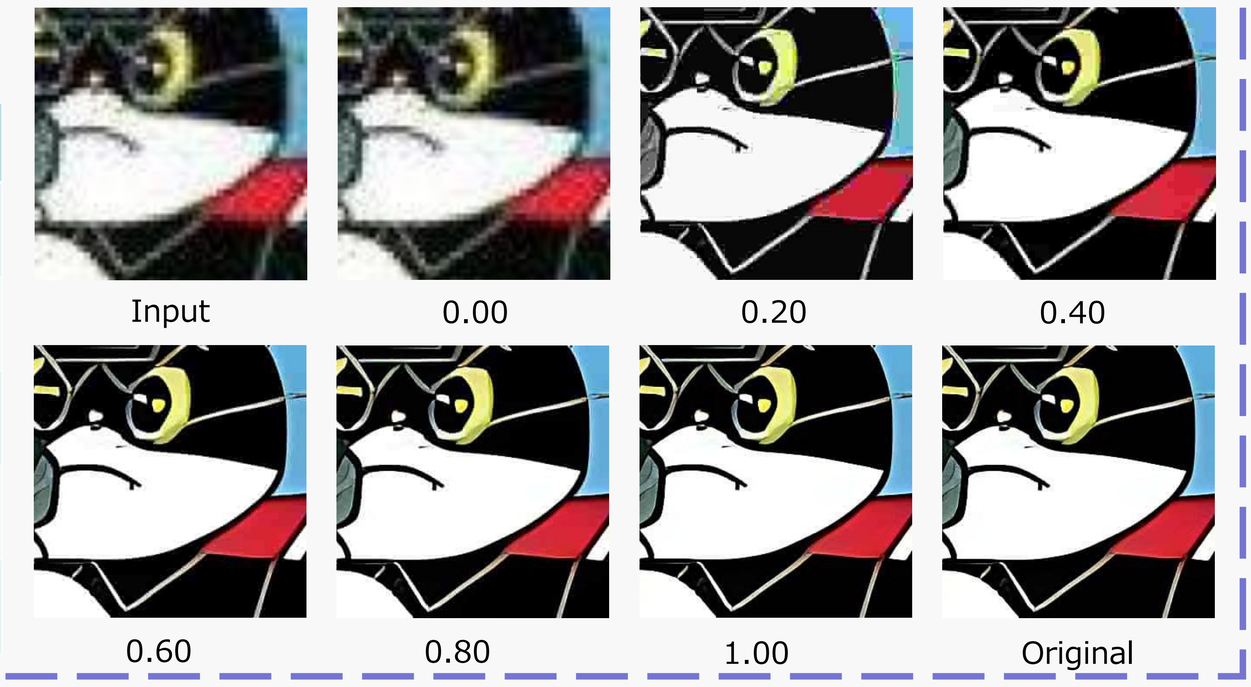
- Scaling factor input guides feature extraction and reconstruction for single model interpolates.
- Perceptual loss and adversarial training with an adaptive scaling to enhance detail preservation.
- Smooth, artifact transition across scaling levels.

Methodology:



Results:

Scale Factor	PSNR ↑	SSIM ↑	LPIPS ↓
0.20	14.20	0.544	0.510
0.40	22.05	0.740	0.395
0.60	28.90	0.805	0.275
0.80	30.78	0.832	0.240
1.00	31.85	0.838	0.190



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RDNet: A Novel Deep Neural Network Based Hybrid Framework for The Diagnosis of Multiple Brain Diseases.

Sworna Akter and Dr. Md. Rubaiyat Hossain Mondal

Abstract

This research proposed a hybrid DL-based model to classify multiple brain diseases like Alzheimer's, sclerosis, stroke, and normal brain and also separately grade Alzheimer's disease. We evaluated the model using three datasets in which dataset1 contains multiple brain diseases, which were collected from multiple sources; datasets2 and 3 were collected from ADNI and OASIS databases. The proposed model is compared with some recent DL-based models and with some existing works on several data samples. The proposed model gives an overall accuracy of 98.97%, 97.67%, and 100% for dataset 1, dataset 2, and dataset 3, respectively. Also evaluate the model on dataset4, which is imbalanced.

Background and Motivation:

Various standalone and hybrid models exist on classification of multiple brain diseases and Alzheimer's disease. Table 1 describes some of them.

Author	Year	Class	No. of images	Disease	Accuracy	Comments
Talo et al.	2019	Four	1074	Multiple	95.23%	Low Accuracy
Siddiqui et al.	2017	Six	310	Multiple	95.7%	Insufficient data
Sorur et al.	2024	Binary	6400	Alzheimer	99.92%	Binary class
Balaji et al.	2023	Five	624	Alzheimer	98.5%	Insufficient data

Table 1: Existing work

There are some research gaps and efficiency of DL models depend on databases, and insufficient data leads to specific demographic characteristics. To increase the performance of the model, models must be more youthful and generalized. So, a new DL based model needs to be developed.

Datasets:

- To get the data unit form, resizing and normalization techniques were applied.
- The train-test ratio was 0.1 using the hold-out method.
- Data augmentation technique also applied. Table 2 describes the whole data set.

Dataset	Database Name	Diseases	No. of images	Class
Dataset1	OASIS, HMS university & Kaggle	Multiple	968	Four
Dataset2	ADNI	Alzheimer	3000	Five
Dataset3	OASIS	Alzheimer	1952	Four
Datase4	OASIS (imbalanced)	Alzheimer	2513	Four

Table 2: Data Sets

Proposed Methodology:

Figure 1 showed the proposed architecture.

- The model is implemented using the concept of two DL-based model.
- This model separately extracts features for the same input, which helps to generalize the output.
- The model is implemented using Google Colaboratory (CoLab).

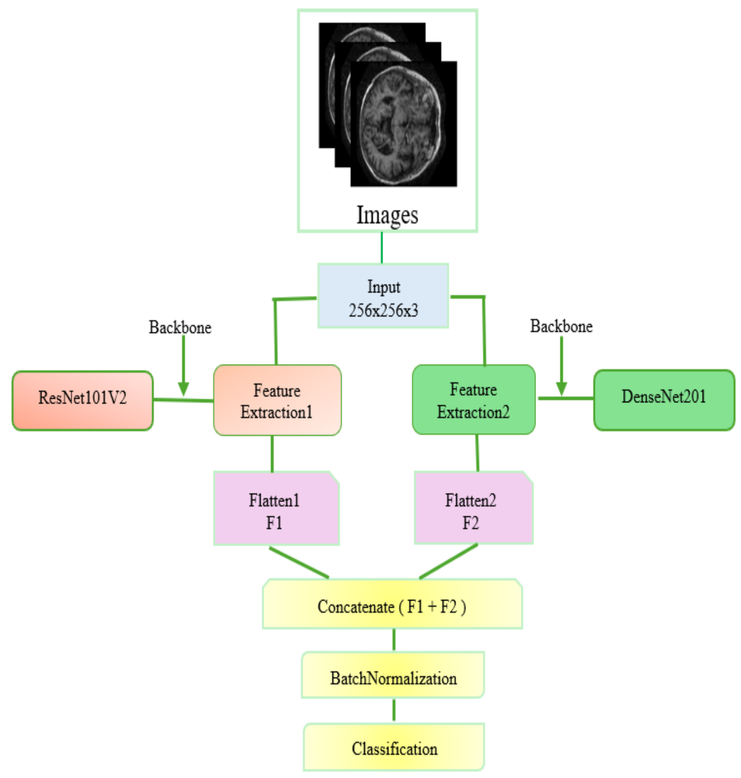

Fig. 1: Proposed RDNet Model Architecture

Results:

Table 3 describes the output of the individual model and hybrid model. For all datasets, the proposed model outperformed the individual model. Figure 2 describes the confusion matrix of the proposed model.

Dataset	DL Models	Model Accuracy	Training Time
Dataset1	ResNet101V2	0.8763	720
	DenseNet201	0.9485	840
	RDNet	**0.9897**	**780**
Dataset2	ResNet101V2	0.9333	2340
	DenseNet201	0.9633	2220
	RDNet	**0.9767**	**2520**
Dataset3	ResNet101V2	0.9490	1620
	DenseNet201	0.9898	1500
	RDNet	**1.0000**	**2220**
Dataset4	ResNet101V2	0.9881	2280
	DenseNet201	0.9960	1980
	RDNet	**1.0000**	**2220**

Table 3: Results of RDNet & standalone modes

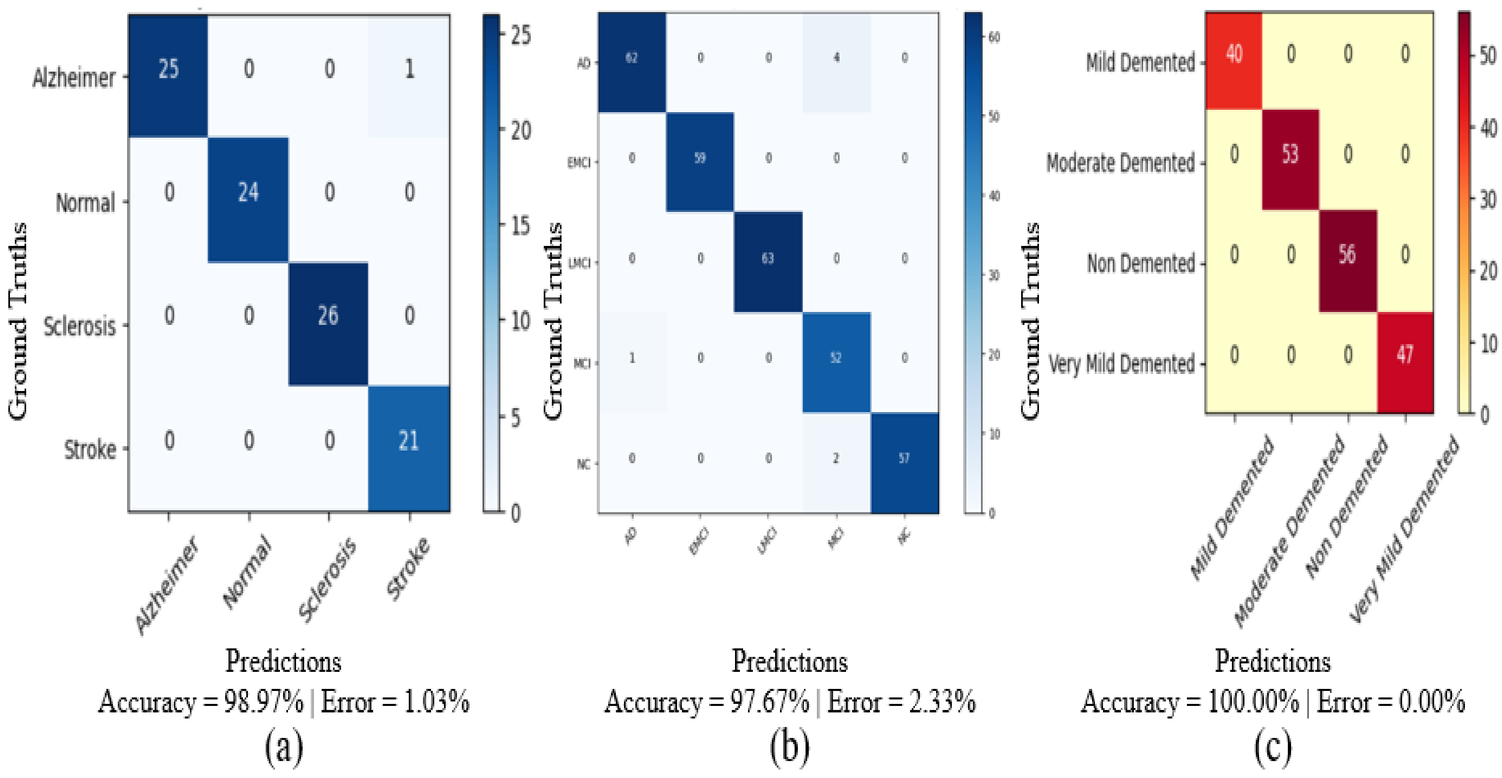

Fig. 2: Confusion matrix of (a) Dataset1, (b) Dataset2, and (c) Dataset3,4

Performance comparison:

Table 4 describes the performance comparison of the proposed model and the existing model on multiple brain diseases, and Table 5 describes the performance comparison of the proposed model and the existing model on Alzheimer's disease.

Author's name and year	No. of Images	Dataset	Class	Referenced model's performance	Proposed model's performance
Nayak et al. [2020]	200	HMS University	Four	97.5%	100%
Talo et al. [2019]	1074		Five	95.23%	96.30%
Siddiqui et al. [2017]	310		Six	95.70%	96.77%

Table 4: Performance comparison of RDNet model with other models on various data samples on multiple brain diseases.

Author's name and year	No. of Images	Dataset	Class	Referenced model's performance	Proposed model's performance
Alshmrany et al. [2023]	3400	ADNI	Five	96.6%	97.45%
Suganthe et al. [2021]	256	Kaggle	Four	79.12%	82.24%
Suganthe et al. [2020]	1000	ADNI	Two	98.67%	100%

Table 5: Performance comparison of RDNet model with other models on various data samples on Alzheimer's disease.