A Project Report

On

Deep Learning based Annotation System for Snowy Weather Road Surface Classification

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Certificate

This is to certify that the project report entitled "Deep Learning based Annotation System for Snowy Weather Road Surface Classification" submitted by Mr Sreevastav Vavilala (Roll No. SE21UARI150), Srujan Reddy (Roll No. SE21UECM060), Vivek Nagisetty (Roll No. SE21UARI195), M. Likith Reddy (Roll No. SE21UCSE115), G. Rithvik Reddy (Roll No. SE21UCSE070), in partial fulfilment of the requirements of the course PR 4203, Project Course, embodies the work done by him/her under my supervision and guidance

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ABSTRACT

Road safety during snow events is a critical challenge, especially in regions susceptible to harsh winters. Timely and accurate detection of snow accumulation levels on roads can aid transportation departments in prioritizing snow removal and enabling safer travel. This project focuses on developing an efficient deep learning-based image classification system that categorizes road conditions into four snow levels: **clear**, **light**, **medium**, and **plowed**.

We utilized transfer learning on three high-performing convolutional neural network architectures: **EfficientNetB3**, **MobileNetV2**, and **ResNet152**. These models were trained on a publicly available snow classification dataset containing over 8,000 labelled images. The dataset exhibited class imbalance, which we addressed through class weighting techniques and augmentation strategies to ensure balanced learning across all categories.

Each model was evaluated based on standard classification metrics—**accuracy**, **precision**, **recall**, and **F1-score**. Among the three, **EfficientNetB3** achieved the highest validation accuracy of **95%**, demonstrating superior performance in both major and minority classes. **ResNet152** followed with an accuracy of **89%**, showing strength particularly in distinguishing medium and plowed snow levels. While **MobileNetV2** achieved a lower accuracy of **79%**, it showed promise for lightweight, real-time deployment in embedded systems.

This project highlights the potential of deep learning in real-time snow detection and road condition monitoring. The findings suggest that transfer learning, coupled with proper class balancing, can yield robust models capable of handling subtle visual differences across snow categories. Our results contribute toward scalable and automated road inspection systems, supporting winter road maintenance efforts and reducing the risk of accidents due to snowy conditions.

CONTENTS

1. INTRODUCTION

1.1 Motivation and Background

Snowfall is a natural phenomenon that, while beautiful, can significantly disrupt transportation infrastructure. Roads covered in snow can cause hazardous driving conditions, delays in emergency services, supply chain interruptions, and increased risk of accidents. According to various transportation safety studies, snow and ice-related road conditions contribute to a substantial number of winter traffic accidents each year, many of which are avoidable with timely intervention and accurate monitoring.

Traditionally, snow monitoring relies on manual reports, weather stations, road sensors, or human inspection by maintenance crews. While effective in localized areas, these methods struggle with scalability, timeliness, and cost-efficiency, especially over large geographical regions or during heavy snowfall events. They often lack real-time feedback and are subject to human error or delay.

With the rapid advancement of artificial intelligence (AI) and the growing accessibility of road-facing cameras (e.g., traffic cams, surveillance systems, and dashboard cameras), there is an untapped opportunity to **automate the detection of snow levels on roads using image-based deep learning models**. This enables instant road condition feedback, scalable snow monitoring, and data-driven decision-making for public safety and infrastructure maintenance.

1.2 Problem Statement

The goal of this project is to develop a computer vision system that can **classify road images into one of four categories based on snow coverage**:

- **Clear** – Road is free of snow.
- **Light** – Road has a light dusting or patchy snow.
- **Medium** – A moderate level of snow that may affect traction and safety.
- **Plowed** – Snow was present but has been partially or fully removed by plowing.

Unlike binary snow detection (snow vs. no snow), our problem requires distinguishing between nuanced levels of snow coverage, which often appear visually similar. This increases the complexity of the classification task and requires robust feature extraction, generalization, and class discrimination capabilities.

1.3 Real-World Applications

1. Road Maintenance and Traffic Control

Local governments and transportation agencies often face logistical challenges in monitoring thousands of kilometers of roads. An automated snow classification system can:

- Alert authorities to roads needing urgent attention
- Optimize snowplow deployment
- Reduce unnecessary road inspections
- Improve traffic flow by prioritizing snow removal

2. Autonomous and Assisted Driving

Autonomous vehicles (AVs) and advanced driver-assistance systems (ADAS) require continuous awareness of road conditions to operate safely. By integrating road snow detection, AVs can:

- Adjust speed or braking behavior
- Modify navigation routes
- Warn drivers about hazardous conditions ahead

3. Public Information Systems

Apps like Google Maps or Waze could use such systems to notify users of snow-covered roads, helping commuters make safer travel decisions.

1.4 Technical Challenges

Despite its potential, the task of snow-level classification from road images presents several technical challenges:

- **Visual Ambiguity:** Differentiating "light" from "medium" snow or "plowed" from "clear" requires models to capture subtle texture and brightness differences.
- **Class Imbalance:** Real-world datasets often contain far more “clear” road images than “light” or “plowed,” causing biased learning unless explicitly addressed with techniques like class weighting or oversampling.
- **Lighting and Weather Variation:** Snow appears different under sunlight, shadows, night lights, fog, or rain. A robust model must generalize across all such conditions.
- **Background Noise:** Vehicles, road signs, and other artifacts can occlude snow or introduce misleading features.
- **Computational Constraints:** While deep learning models can be highly accurate, deployment on edge devices demands efficient, lightweight architectures.

1.5 Proposed Solution

To tackle these challenges, we explore **transfer learning** using three state-of-the-art convolutional neural network architectures:

- **EfficientNetB3:** Known for its optimal accuracy-to-efficiency ratio.
- **MobileNetV2:** A lightweight model ideal for real-time deployment on resource-constrained hardware.
- **ResNet152:** A deeper model capable of learning fine-grained patterns and hierarchical features.

We train and validate these models on a well-labeled image dataset using strategies such as:

- Data augmentation (rotation, flipping, zoom)
- Class weighting to mitigate imbalance
- Model fine-tuning with frozen and unfrozen layers
- Evaluation using precision, recall, F1-score, and confusion matrix

The final objective is to determine which model offers the best performance trade-off for practical use cases, and how well these models generalize across snow categories in unseen images.

2. PROBLEM DEFINITION

The rapid development of computer vision has opened up opportunities to automate many safety-critical tasks in transportation. One such task is the classification of road conditions during snow events. Snow accumulation poses a significant hazard to drivers, yet there is currently no widely adopted, automated method for assessing snow severity from visual data.

This project addresses the problem of **automated snow-level classification** from road images using deep learning. Unlike binary classification (snow vs. no snow), this project tackles the more nuanced challenge of distinguishing between different levels of snow coverage—**clear**, **light**, **medium**, and **plowed**. Accurate classification at this level can significantly improve decision-making in road maintenance, driver assistance systems, and traffic management.

2.1 Key Questions Addressed

This project is designed to answer the following core questions:

1. Can we accurately classify road conditions into snow levels using deep learning?

This is the fundamental question driving the project. While object classification in images is a well-established problem, snow-level classification introduces unique visual subtleties that require careful model design and training. The goal is to train models to make this decision accurately based on visual cues.

2. How do different CNN architectures compare in terms of accuracy and efficiency?

We evaluate three transfer learning models: **EfficientNetB3**, **MobileNetV2**, and **ResNet152**. Each has different strengths—EfficientNet offers a balance between speed and accuracy, MobileNet is designed for resource-limited deployment, and ResNet152 is a high-capacity model ideal for complex feature extraction.

3. Can the model generalize across varying conditions like lighting, road material, and camera angle?

Real-world images vary due to environmental and camera factors. A useful model must generalize to these conditions, not just memorize training examples. We test models against unseen images with varying shadows, vehicle occlusions, and snow textures.

4. How can we address class imbalance to ensure performance across all categories?

The dataset is inherently imbalanced—there are more "clear" road images than "plowed" or "light" ones. This can lead to biased predictions if not handled carefully. The project applies techniques such as **class weighting** and **data augmentation** to reduce this bias.

2.2 Problem Explanation in Simple Terms

Think of a winter morning where transportation officials need to know the condition of thousands of roads. Rather than sending personnel or relying solely on road sensors, they could analyze camera feeds. If a system can classify each road image into a specific snow category, they can prioritize roads needing plowing or salting.

From the perspective of the AI model, it must look at an image and decide:

- Is the road **completely clear**?
- Is there a **thin layer of snow**, maybe just starting to accumulate?
- Is the road **moderately covered**, posing a hazard?
- Has it been **plowed**, with partial snow or slush still present?

This decision-making must be fast, reliable, and adaptable to thousands of images captured under different conditions. The complexity arises from the similarity in appearance between these categories and from inconsistent real-world lighting or partial snow coverage.

2. 3 Mathematical Representation of the Problem

Let us define the problem in terms of supervised learning and classification:

- Let $\mathbf{X} = \{x_1, x_2, ..., x_n\}$ be a set of input images, where each $x_i \in R^{h\times w\times 3}$ is a colour image with height h, width w, and 3 colour channels (RGB).
- Let $\mathbf{Y} = \{y_1, y_2, ..., y_n\}$ be the corresponding set of labels, where each $y_i \in \{0,1,2,3\}$ represents one of the four classes:
    - 0: Clear
    - 1: Light
    - 2: Medium
    - 3: Plowed

The goal is to learn a function f **:** $\mathbf{X} \rightarrow \mathbf{Y}$ that maps an input image x to its corresponding snow-level label y. This function is learned by minimizing a loss function $\mathcal{L}$ **(f(x), y)** commonly categorical cross-entropy, over a training dataset.

The optimal model $\mathbf{f}^*$ is then:

$$\mathbf{f^*=arg\ min}\frac{1}{n}\sum_{i=0}^{n}\mathcal{L}(\mathbf{f}(\mathbf{xi}), \boldsymbol{yi})$$

Where:

- $\mathcal{L}$ is the softmax cross-entropy loss,
- n is the number of training examples.

The final prediction for an unseen image x_{test} is:

$\hat{y}$=arg max $f_k(x_{test})$

Where $f_k(x_{test})$ is the predicted probability of class k∈{0,1,2,3}.

2.4 Summary

In summary, this project addresses a real and impactful problem by:

- Designing a machine learning pipeline for multi-class snow classification
- Comparing three advanced neural architectures
- Handling imbalanced data with real-world variability
- Offering a deployable solution for smart transportation systems

The combination of accurate classification and efficient computation makes this work relevant not just academically, but for deployment in practical road-monitoring and winter traffic management systems.

3. BACKGROUND AND RELATED WORK

3.1 Road Surface Condition Classification Using Deep Learning

Cheng et al. presented a convolutional neural network (CNN)-based system to classify road surface conditions using five categories: dry, wet, snowy, muddy, and others. A key innovation in this study was the introduction of a **custom activation function** called **Gai-ReLU**, designed to improve the performance of standard ReLU-based networks. They tested their models on the Oxford RobotCar and KITTI datasets and achieved a classification accuracy of **94.89%**.

Key Contributions

- Introduced a novel **Gai-ReLU** activation function combining ReLU and SoftSign characteristics to improve convergence and performance.
- Conducted thorough experiments comparing multiple activation functions (ReLU, leaky ReLU, SoftMax, TanH, etc.) and machine learning baselines (SVM, BP neural network).
- Achieved performance improvements not just in accuracy but also in generalization and inference time.

Limitations

- The model classifies **generic surface types** but does not specialize in snow subcategories such as light, medium, or plowed, which are crucial for winter road safety decisions.
- The dataset size was moderate, and class balancing methods were not deeply addressed.
- Although activation function innovation is notable, architectural improvements or efficiency for deployment (e.g., MobileNet) were not explored.

Relevance to Our Work
Our project extends this work by:

- Focusing **specifically on snow conditions** and classifying road images into four finely detailed snow categories: **clear, light, medium, and plowed**.
- Employing **transfer learning** with three state-of-the-art pretrained CNNs (EfficientNetB3, MobileNetV2, and ResNet152), each optimized for different deployment environments (cloud vs. edge).
- Using **class weighting and data augmentation** to address class imbalance, which was not emphasized in Cheng et al.'s study.
- Comparing **accuracy and deployment readiness**, where we find EfficientNetB3 achieves higher accuracy (95%) while MobileNetV2 is more suited for real-time use.

3.2 Weather and Surface Condition Detection Using Roadside Webcams

This study presents a sophisticated and cost-effective approach to classify both **weather conditions** (clear, light snow, heavy snow) and **road surface conditions** (dry, snowy, wet/slushy) using images from roadside webcams. The authors apply **transfer learning** with pre-trained CNN models—**AlexNet**, **GoogLeNet**, and **ResNet18**—to classify over 15,000 annotated images collected from Interstate-80 in Wyoming. The best-performing model, **ResNet18**, achieved an accuracy of **97.3%** for weather and **99.1%** for surface condition classification.

Key Contributions

- The study demonstrates the **real-world applicability** of pre-trained CNNs for deployment in Traffic Management Centers (TMCs).
- It leverages **existing infrastructure (CCTV webcams)**, significantly reducing hardware costs compared to RWIS installations.
- It incorporates a comprehensive evaluation using **7 performance metrics** (accuracy, precision, recall, F1-score, etc.).
- The annotated dataset is carefully constructed from 56 webcam locations over five months, ensuring reliability and diversity.

Limitations

- While the study distinguishes between "light" and "heavy" snow, it does **not include "plowed" roads**—a critical class for operational decisions.
- The model classifies both weather and surface conditions, but **does not explicitly explore architectural comparisons beyond ResNet18 and GoogLeNet**.
- The camera angles and geographic coverage are limited to a single U.S. state, potentially affecting **generalizability**.

Relevance to Our Work
Our project builds on this work in several important ways:

- We extend classification to **four snow-specific categories**: clear, light, medium, and plowed—providing **finer granularity** for road safety and winter maintenance applications.
- We benchmark **EfficientNetB3**, **MobileNetV2**, and **ResNet152**, offering a broader architectural comparison and emphasizing **efficiency vs. performance** for deployment flexibility.
- We evaluate not only **classification metrics**, but also the impact of **class imbalance** using weighted training.
- While Khan & Ahmed used a **limited set of pre-trained models**, our work explores **lightweight models like MobileNetV2** suitable for embedded use (e.g., dashcams, drones, edge devices).

3.3 DeepReject and DeepRoad – Road Condition Recognition Under Adversarial Conditions

In this paper, Sakaino proposes a robust dual-module system for road condition recognition under extreme environmental noise using two components: **DeepReject** and **DeepRoad**. The innovation lies in addressing **adversarial conditions**—fog, low light, lens glare, and strong illumination—which are often overlooked in road scene classification.

Key Contributions

- **DeepReject** filters out images with low visibility or poor lighting using an image quality assessment system before classification. It rejects frames with glare, heavy fog, or lens reflection using a lightweight classifier (VGG19).
- **DeepRoad** uses a **Transformer-based semantic segmentation model (SegFormer)** to classify road scenes into up to **seven distinct conditions** (e.g., dry, wet, black sherbet, white sherbet, snow cover, compacted snow, frozen).
- Introduces a new dataset with both **real and synthetic adversarial conditions**, and demonstrates improved performance over CNN-based baselines like FCN.
- The combined system boosts classification accuracy by over 10% compared to standalone models, especially under poor visibility.

Limitations

- The model primarily focuses on **semantic segmentation**, not classification from static images, which is the focus of our project.
- The system is **heavily optimized for rejecting low-quality frames**, but in real-time systems, discarding images could reduce temporal information available for decision-making.
- Training and evaluation rely on custom datasets, making comparison with other public benchmarks difficult.

Relevance to Our Work

- This paper highlights the importance of addressing **adverse weather conditions**, which we partially tackle via **data augmentation** and **class weighting**.
- Unlike DeepRoad, which uses semantic segmentation and transformers, our approach focuses on **image-level classification** using **EfficientNetB3**, **MobileNetV2**, and **ResNet152**. This makes our model more applicable to real-time applications with limited compute capacity (e.g., on edge devices or embedded systems).

- Their seven-class taxonomy includes fine-grained snow categories (e.g., “compacted snow” vs. “frozen”), which validates the need for **multi-class snow-level distinction**—the same motivation behind our four-class (clear, light, medium, plowed) system.

3.4 Winter Road Surface Condition Recognition Using a Pre-Trained Deep CNN

Pan et al. investigated the use of a **pre-trained VGG16 CNN** for classifying winter road surface conditions into multiple levels: bare, partly snow-covered, and fully snow-covered. The research addressed a key challenge in transportation: how to automate RSC (Road Surface Condition) detection using low-cost, scalable technologies such as smartphone and in-vehicle cameras.

Key Contributions

- Demonstrated that **pre-trained deep CNNs**, when fine-tuned with a small domain-specific dataset, can **outperform traditional ML methods** like Random Forests, ANN, and SVMs.
- Achieved testing accuracy of **90.7%** in a binary classification (snow vs. no snow) setting and **87.3%** for a three-class setup.
- Conducted extensive **sensitivity analysis** on learning rate, number of trainable layers, and model structure, proving that proper fine-tuning can boost performance without full retraining.
- Introduced the idea of **partial layer freezing**, where early CNN layers are frozen and only higher-level layers are retrained for efficiency and generalization.

Limitations

- Despite the solid overall accuracy, **classification of fully snow-covered surfaces** achieved only 56.3% accuracy—highlighting difficulty in identifying **extreme snow conditions**, especially when data samples are few.
- **Only one architecture (VGG16)** was tested. More recent and efficient networks like EfficientNet or MobileNet were not considered.
- Dataset size was limited, and generalization across different weather, lighting, or geographic conditions remains uncertain.

Relevance to Our Work
Our project builds on and extends this work by:

- Evaluating multiple **modern CNN architectures**: EfficientNetB3 (accurate and efficient), ResNet152 (deep and powerful), and MobileNetV2 (lightweight and deployable).
- Using a **4-class snow categorization**: clear, light, medium, and plowed—offering **more detailed classification** than the 3-class model in Pan et al.'s work.

- Applying **class weighting** and **data augmentation** to handle imbalance and improve recall for minority classes like plowed or light snow.
- Demonstrating higher class-level accuracy and overall model performance (EfficientNetB3 reached **95% accuracy**) using fewer resources, suggesting readiness for **real-world deployment**.

3.5 EfficientNet — Rethinking Model Scaling for CNNs

This seminal paper introduces **EfficientNet**, a family of convolutional neural networks that significantly outperform earlier models (e.g., ResNet, Inception, NASNet) in both **accuracy and computational efficiency**. The key innovation is a novel **compound scaling method** that uniformly scales a baseline model's width, depth, and input resolution using a **set of predefined coefficients**. EfficientNet models achieve state-of-the-art accuracy on ImageNet while requiring **10x fewer parameters and FLOPS** than previous best-performing models.

Key Contributions

- Developed a **compound scaling formula**:

$$\text{depth}=\boldsymbol{\alpha}^{\phi},\ \text{width}=\boldsymbol{\beta}^{\phi},\ \text{resolution}=\boldsymbol{\gamma}^{\phi},\ \text{with } \alpha\cdot\beta^2\cdot\gamma^2\approx 2$$

This ensures balanced and principled scaling rather than arbitrary increases in model size.

- Used **neural architecture search (NAS)** to design a mobile-sized baseline model (EfficientNet-B0), which was scaled up to larger variants (B1–B7) using the compound scaling rule.
- Demonstrated superior performance: EfficientNet-B7 achieved **84.3% top-1 accuracy** on ImageNet while being **8.4x smaller and 6.1x faster** than GPipe, a prior state-of-the-art model.
- Validated transfer learning performance on **eight diverse datasets**, where EfficientNet variants consistently achieved better accuracy with **fewer parameters**, proving robustness and generalizability.

Limitations

- EfficientNet requires **careful fine-tuning** for domain-specific tasks (e.g., road conditions), especially when pretrained on datasets like ImageNet that do not include snow imagery.
- Larger variants (e.g., B5–B7) can still be computationally heavy for **low-power edge devices** unless further optimized.

Relevance to Our Work

- This paper **directly informs our choice** to use **EfficientNetB3**, balancing performance and efficiency, and fine-tuning it for snow-level image classification.

- The **compound scaling method** aligns perfectly with our goal of deploying models across diverse platforms—from cloud-based TMC systems to on-device dashcams.
- Compared to earlier models like VGG16 or ResNet152, EfficientNetB3 requires **fewer parameters (~12M)** and FLOPS while achieving **higher accuracy (95%)** on our multi-class snow classification task.
- Our use of EfficientNet builds on this work by applying it to a **highly specialized real-world problem**—classifying **clear, light, medium, and plowed** road conditions during winter weather.

4. IMPLEMENTATION

The goal of this project is to classify road images into four categories based on the amount of snow present: **clear**, **light**, **medium**, and **plowed**. The classification is performed using multiple convolutional neural network (CNN) models, including EfficientNetB3, MobileNetV2, and ResNet152. This section provides a detailed overview of the implementation strategy, covering data preprocessing, model selection, evaluation, and testing.

4.1 Data Collection and Preprocessing

The initial step in the project was acquiring and preparing the dataset. The dataset, sourced from Kaggle, contains labelled images representing the four road conditions. These images are organized in class-based folders.

The preprocessing phase involved several key steps:

1. **Image Resizing and Normalization**:
   All images were resized to 224×224×3 pixels to match the input requirements of the selected models. Pixel values were normalized to fall within the [0, 1] range for consistent input scaling.

2. **Data Augmentation**:
   To increase dataset diversity and mitigate overfitting, the following augmentations were applied using the ImageDataGenerator API:

   - Rotation (±20 degrees)
   - Width/Height shift (±20%)
   - Zoom range (0.8–1.2)
   - Horizontal flip
   - Shearing

3. **Class Imbalance Handling**:
   The dataset had more examples of “clear” and “medium” classes than “light” and “plowed.” To address this:

   - Class weights were computed using sklearn.utils.compute_class_weight.
   - Minority classes were augmented more heavily to balance training input.

4. **Train/Validation Split**:
   The dataset was split into 80% for training and 20% for validation using stratified sampling to maintain class distribution.

4.2 Model Selection

Multiple CNN architectures were selected to evaluate performance across different computational and accuracy profiles:

1. **EfficientNetB3**:
   Used as a high-performing, scalable model. Pretrained on ImageNet, it was fine-tuned in two phases:
   - Phase 1: Base layers frozen; classifier head trained.
   - Phase 2: All layers unfrozen and fine-tuned with a low learning rate.
2. **MobileNetV2**:
   Chosen for its lightweight design and suitability for deployment on edge devices (e.g., smart cameras, embedded systems). It was trained with dropout and regularization to reduce overfitting.
3. **ResNet152**:
   Selected for its depth and ability to learn complex patterns. All layers were trained end-to-end, allowing for deeper feature learning.

4.3 Model Evaluation

Each model was evaluated using standard classification metrics:

1. **Accuracy**: Overall correct predictions over total predictions.
2. **Precision, Recall, and F1-score**:
   These metrics were calculated per class to assess how well each model handles class imbalance and generalization.
3. **Confusion Matrix**:
   Visualized misclassification trends (e.g., frequent confusion between “plowed” and “light” categories).

4.4 Conclusion and Future Work

This implementation successfully applied transfer learning to classify snow levels on roads using high-performance CNN models. EfficientNetB3 demonstrated superior accuracy, while MobileNetV2 offered a lightweight alternative for deployment.

Future work could focus on:

- **Real-time inference**: Implementing MobileNetV2 on embedded systems (e.g., NVIDIA Jetson, Raspberry Pi).
- **Multimodal inputs**: Incorporating additional weather data (e.g., temperature, humidity) to improve predictions.
- **Video-based classification**: Extending from static images to temporal sequences for smoother and more robust classification.
- **Geographically diverse datasets**: Enhancing generalizability by training on images from various regions and climates.

5. RESULTS

The primary goal of this project was to implement and evaluate various deep learning models for multi-class image classification of road conditions based on snow coverage. The models considered were **EfficientNetB3**, **MobileNetV2**, and **ResNet152**—each representing a different trade-off between accuracy, computational cost, and real-time feasibility.

Each model was evaluated using standard classification metrics: **accuracy**, **precision**, **recall**, and **F1-score**. The results are summarized in the table below, followed by a discussion of individual model performance and their strengths and limitations.

Table 1: Classification Report of EfficientNet

	Precision	**Recall**	**F1-Score**
Clear	0.99	0.98	0.99
Light	0.76	0.90	0.83
Medium	0.97	0.92	0.95
Plowed	0.83	0.94	0.88

Accuracy of EfficientNet Model: 95%

Table 2: Classification Report of MobileNet

	Precision	**Recall**	**F1-Score**
Clear	0.93	0.84	0.88
Light	0.50	0.62	0.55
Medium	0.89	0.78	0.83
Plowed	0.38	0.69	0.49

Accuracy of MobileNet Model: 79%

Table 3: Classification Report of ResNet

	Precision	Recall	F1-Score
Clear	0.98	0.97	0.97
Light	0.79	0.60	0.68
Medium	0.90	0.88	0.89
Plowed	0.59	0.80	0.68

Accuracy of ResNet Model: 89%

EfficientNetB3

EfficientNetB3 demonstrated the best overall performance with **95% accuracy**. It effectively captured subtle variations between similar classes like "light" and "plowed" snow. It also showed strong balance across all four categories, indicating good generalization. Its compound scaling and fine-tuning strategy likely contributed to its robustness.

ResNet152

ResNet152 achieved a strong accuracy of **89%**, particularly excelling in distinguishing between "medium" and "plowed" snow. However, its depth and size made training slower and more memory-intensive. It also showed slightly lower precision and recall in identifying "light" snow compared to EfficientNetB3.

MobileNetV2

With an accuracy of **79%**, MobileNetV2 was the most lightweight and fastest model but showed performance trade-offs, especially in misclassifying "plowed" and "light" snow. Despite its lower accuracy, it is ideal for deployment in **resource-constrained environments** like smart cameras or mobile systems.

6. CONCLUSION

This project successfully explored the application of deep learning for **multi-class image classification** of snow levels on roads, with the goal of aiding road maintenance, traffic safety, and intelligent transportation systems. The classification task involved distinguishing between four visually similar road conditions—**clear**, **light**, **medium**, and **plowed**—which presented both technical and practical challenges due to class imbalance, environmental variability, and the subtle nature of snow textures.

To address this, we implemented and evaluated three state-of-the-art convolutional neural networks:

- **EfficientNetB3**
- **MobileNetV2**
- **ResNet152**

All models were trained using transfer learning on a labeled dataset of road images. Techniques such as **data augmentation**, **class weighting**, and **fine-tuning** were used to enhance generalization and overcome class imbalance.

Among the models:

- **EfficientNetB3** achieved the best performance with **95% accuracy**, demonstrating superior generalization and balanced class-wise performance.
- **ResNet152**, while slightly less accurate (**89%**), showed strong performance in identifying more snow-covered classes.
- **MobileNetV2**, although having the lowest accuracy (**79%**), is well-suited for deployment in **resource-constrained, real-time environments**.

The results underscore the importance of model selection based on application requirements. While EfficientNetB3 is ideal for high-accuracy tasks, MobileNetV2 is more applicable in embedded systems or edge devices.

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