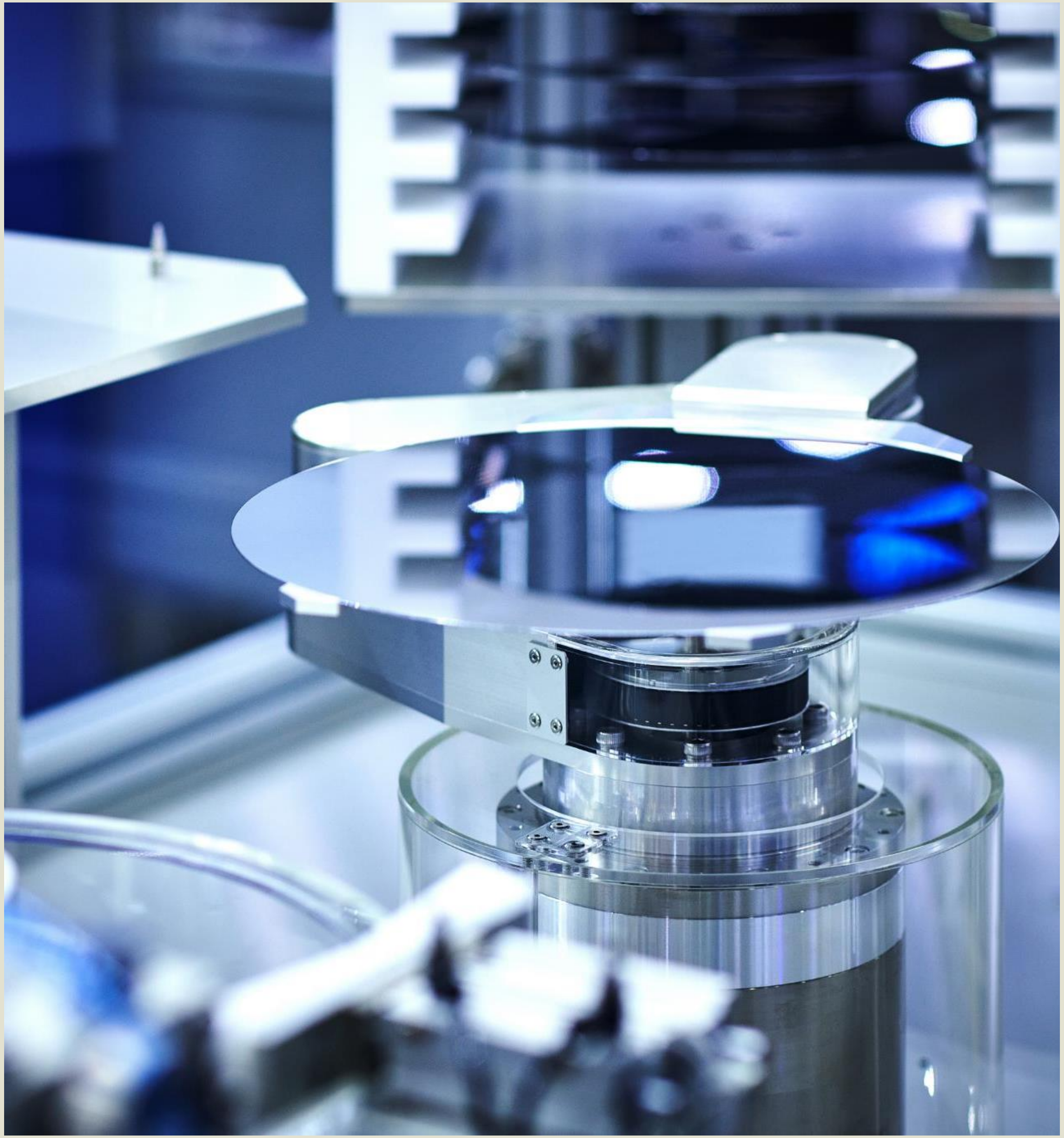
Project – Rock Classification with a RAMAN Spectrometer

By Tanmay Talreja (m12519565)



Introduction to Mineral Classification

Challenges of Traditional Methods

Manual inspection and classical Raman spectroscopy are slow, error-prone, and need expert interpretation in industrial settings.

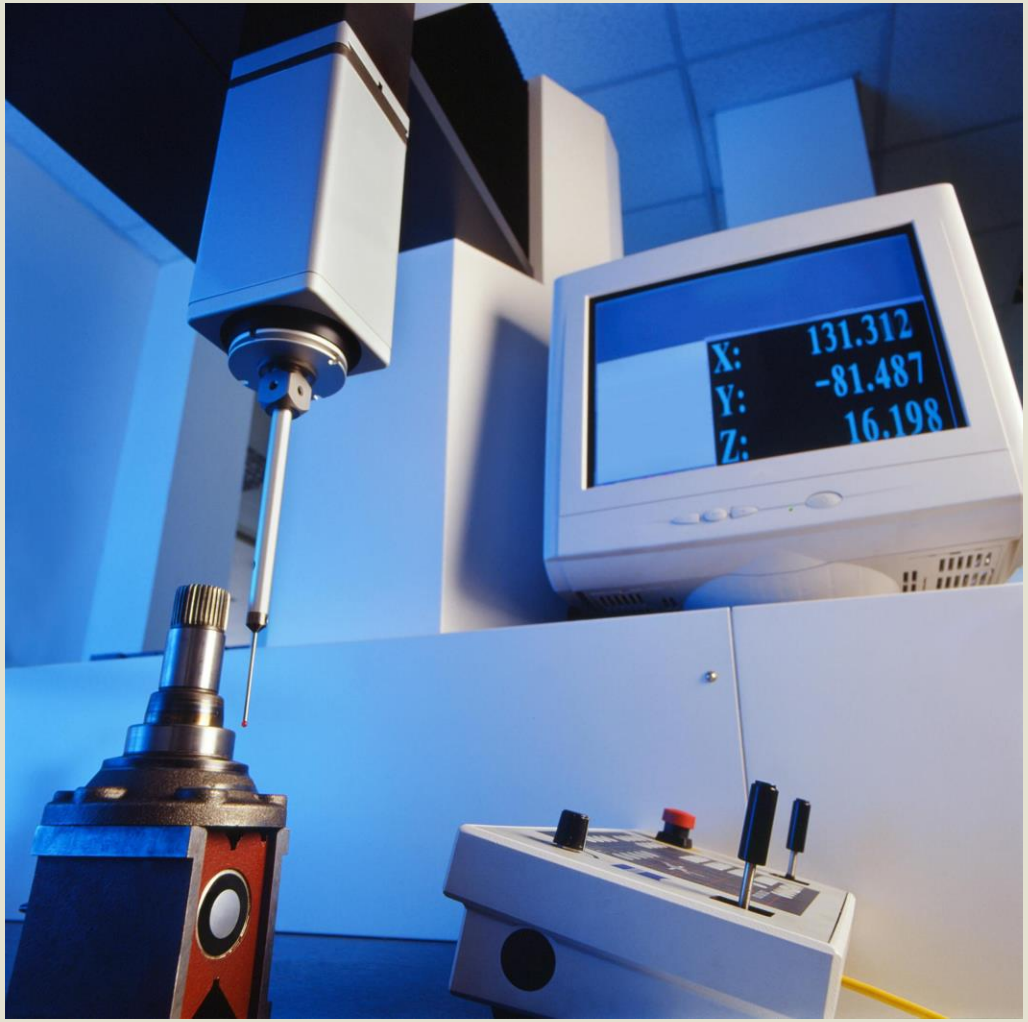
AI Integration Benefits

Integrating AI automates mineral classification, improving speed, accuracy, and reducing manual feature extraction dependency.

Raman Spectroscopy Advantages

Raman sensors provide detailed molecular fingerprints offering superior chemical insights beyond surface-level imaging.

Project Objectives



Preference for Raman Spectroscopy

Raman spectroscopy is favored over traditional camera sensors for accurate mineral classification due to its specificity and sensitivity.

Limitations of Classical Methods

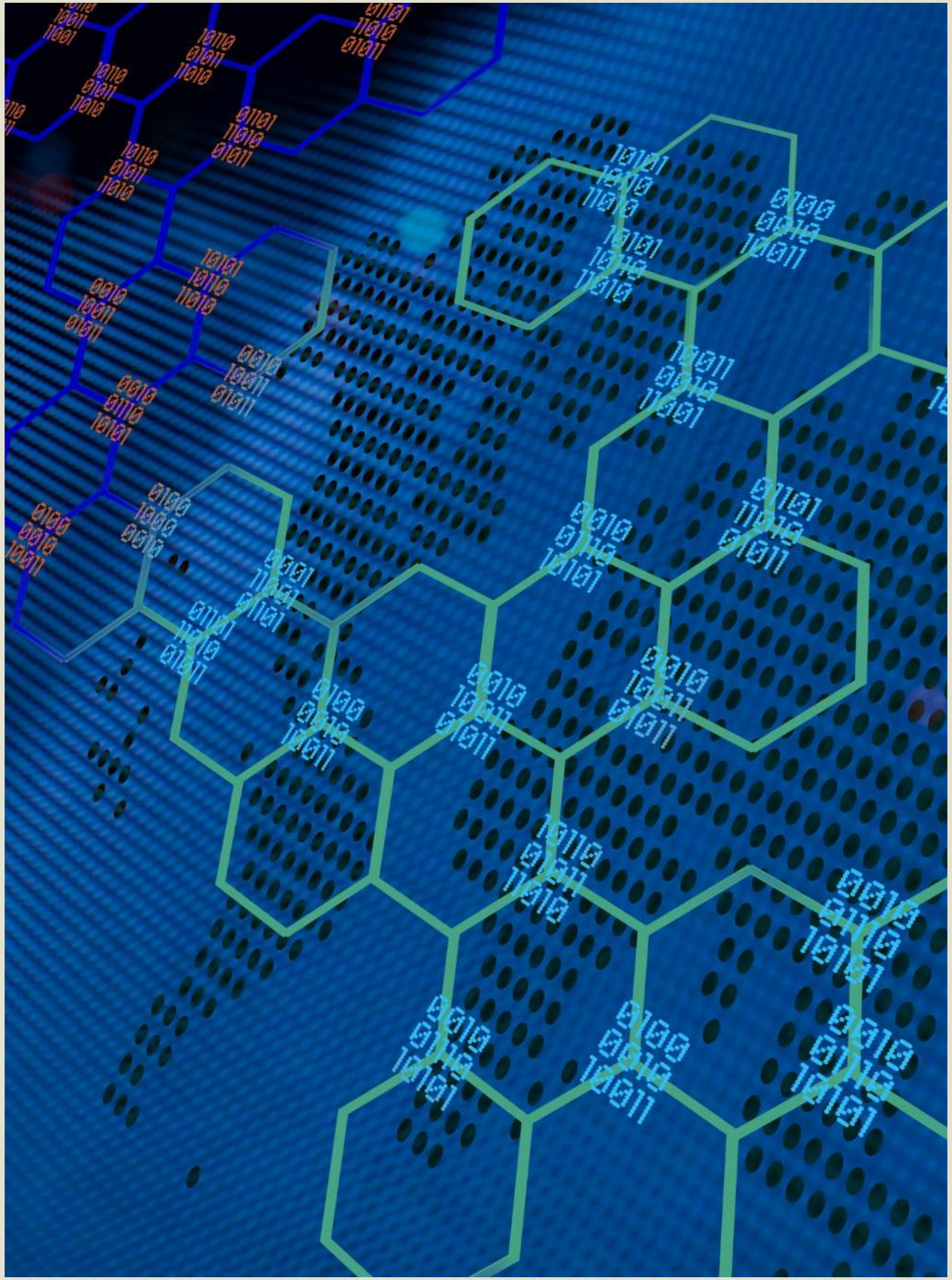
Classical Raman classification methods face challenges like noise sensitivity and overlapping spectral peaks affecting accuracy.

Machine Learning Application

Machine learning models automate feature extraction and classification of Raman spectral data for enhanced analysis.

Comparing Learning Approaches

Spectral image-based (30 fps & 1 fps) and spectral profile-based learning(30 fps &1 fps) are compared for accuracy, efficiency, and scalability.



Why Raman Spectroscopy?

Chemical Composition Analysis

Raman spectroscopy captures molecular-level chemical information beyond surface color and texture, enabling accurate mineral identification.

Superior to Camera Sensors

Unlike cameras, Raman sensors avoid misleading visual similarities by focusing on chemical differences in minerals.

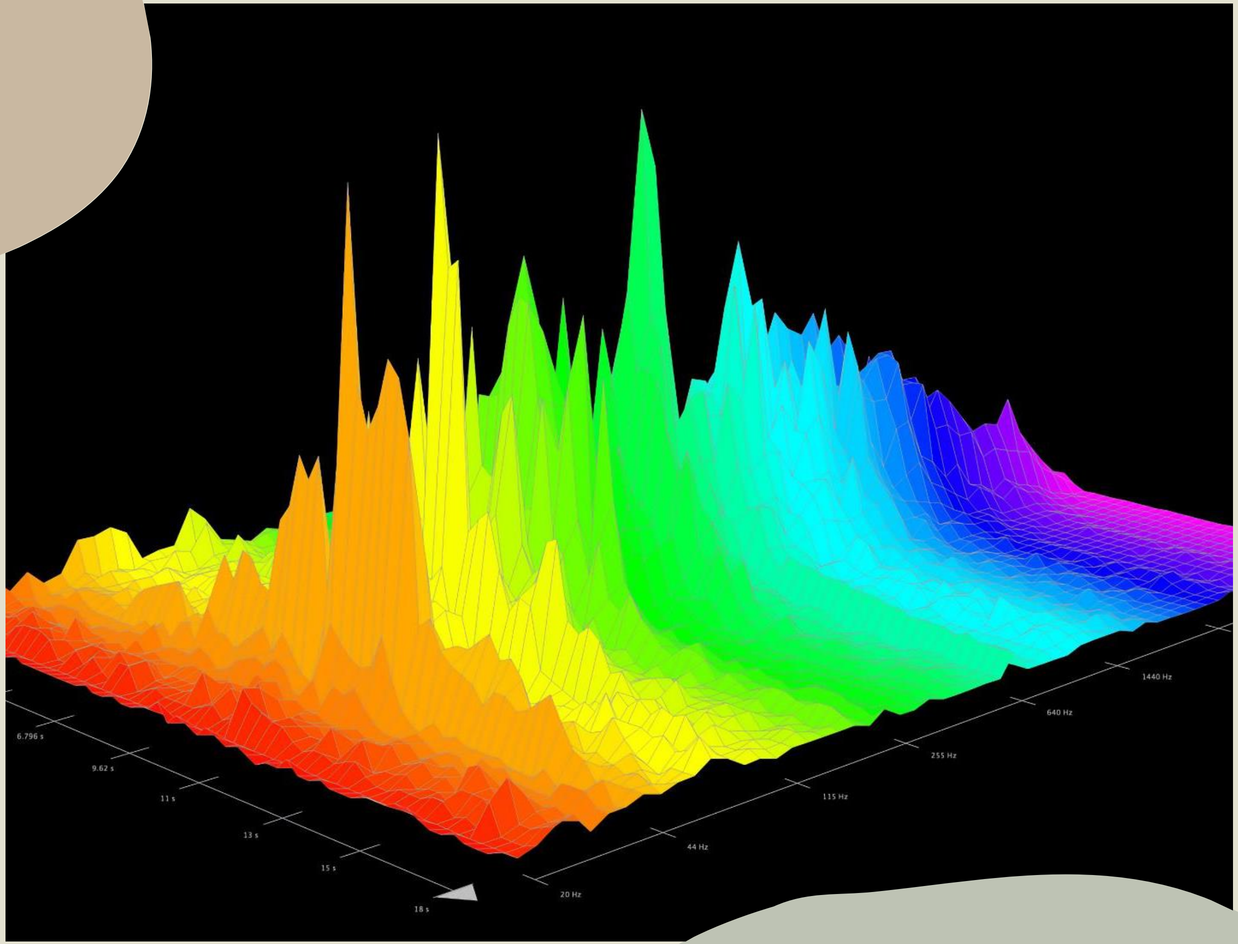
Robustness to Environment

Raman spectroscopy maintains accuracy despite lighting changes and surface contamination, unlike optical imaging methods.

Integration with AI

Raman spectroscopy's precise data is ideal for AI-driven classification, enhancing resilience and accuracy in diverse environments.

Data Modalities and Preprocessing



Mineral Classes and Data Types

The dataset contains seven mineral classes using spectral images and normalized spectral profiles as data modalities.

Spectral Image Processing (30fps & 1fps)

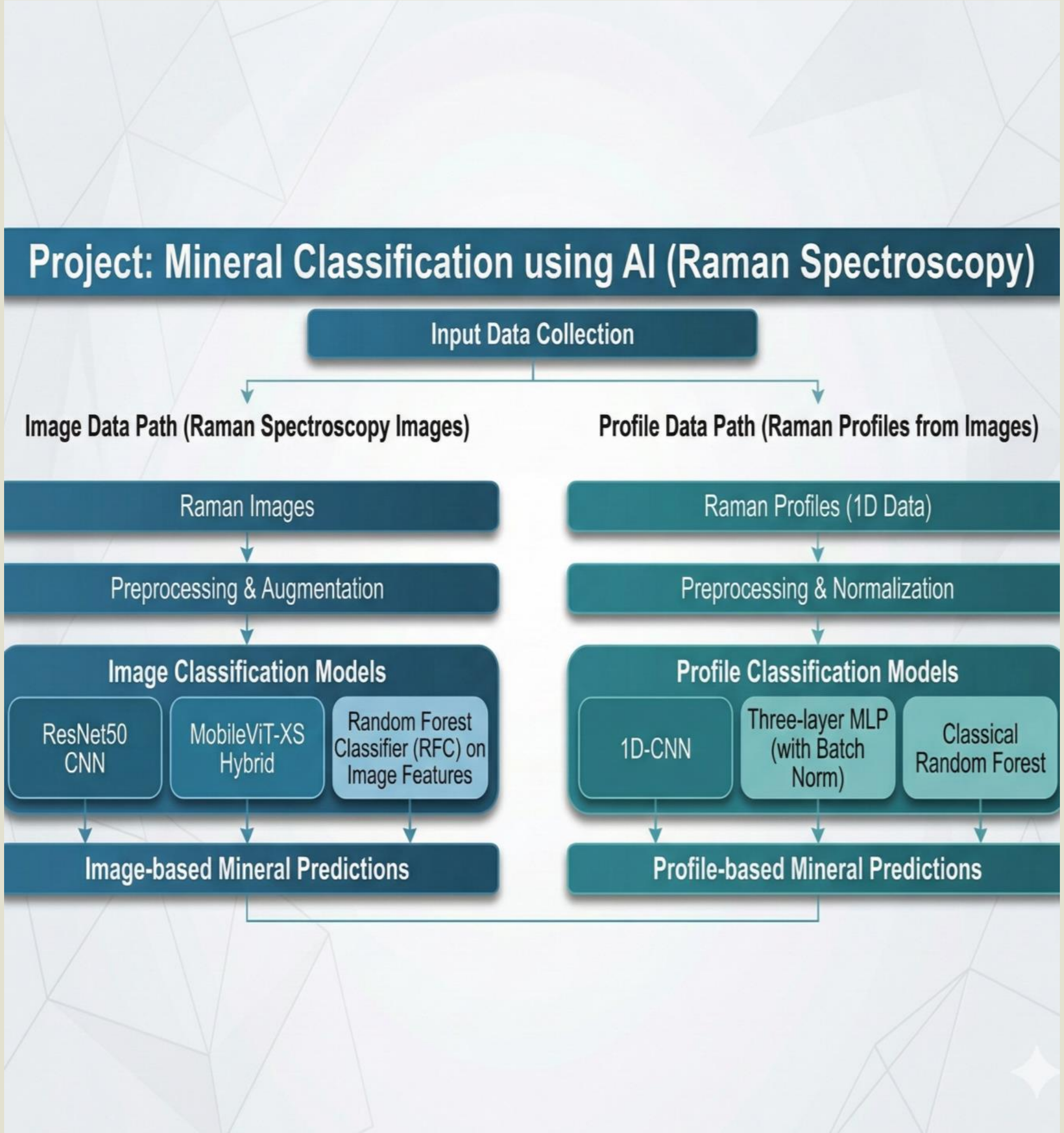
Spectral images were resized and converted into RGB tensors suitable for deep learning models for both 30 fps and 1fps.

Normalized Spectral Profiles (30fps & 1fps)

Normalized Raman intensity profiles captured one-dimensional measurements across wavelengths in CSV format for both 30 fps and 1 fps.

Preprocessing Techniques

Normalization, label encoding, and train-test splitting were used to prepare data for model training.



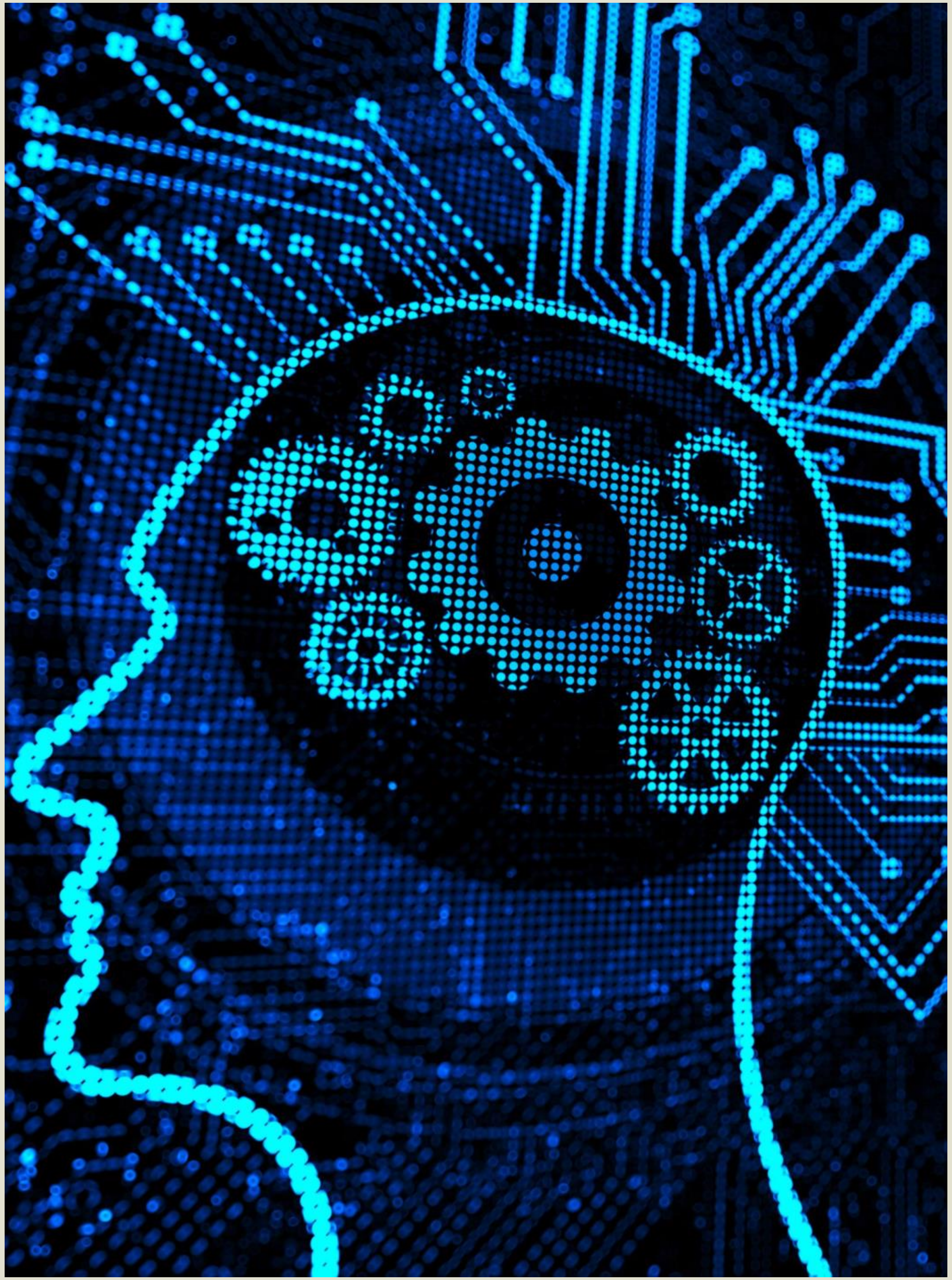
Architectures for Image and Profile Data

Image Models

ResNet50 CNN, MobileViT-XS hybrid model and Random Forest on flattened images for image classification.

Profile Models

1D-CNN uses Conv1d and AdaptiveMaxPool1d layers for feature extraction from profiles .Three-layer MLP with batch normalization and dropout. Along with classical Random Forest baseline for profile classification.



Training Configuration and Strategy

Supervised Learning Setup

Models were trained using supervised learning with clear labeled mineral classes to ensure accurate classification.

Training Parameters

Adam optimizer with 0.0001 learning rate and batch sizes of 8 for images and 16 for profiles were used during training.

Optimization and Early Stopping

Training ran up to 10 epochs for profiles and 5 for images with early stopping at 100% accuracy to save computational resources efficiently.

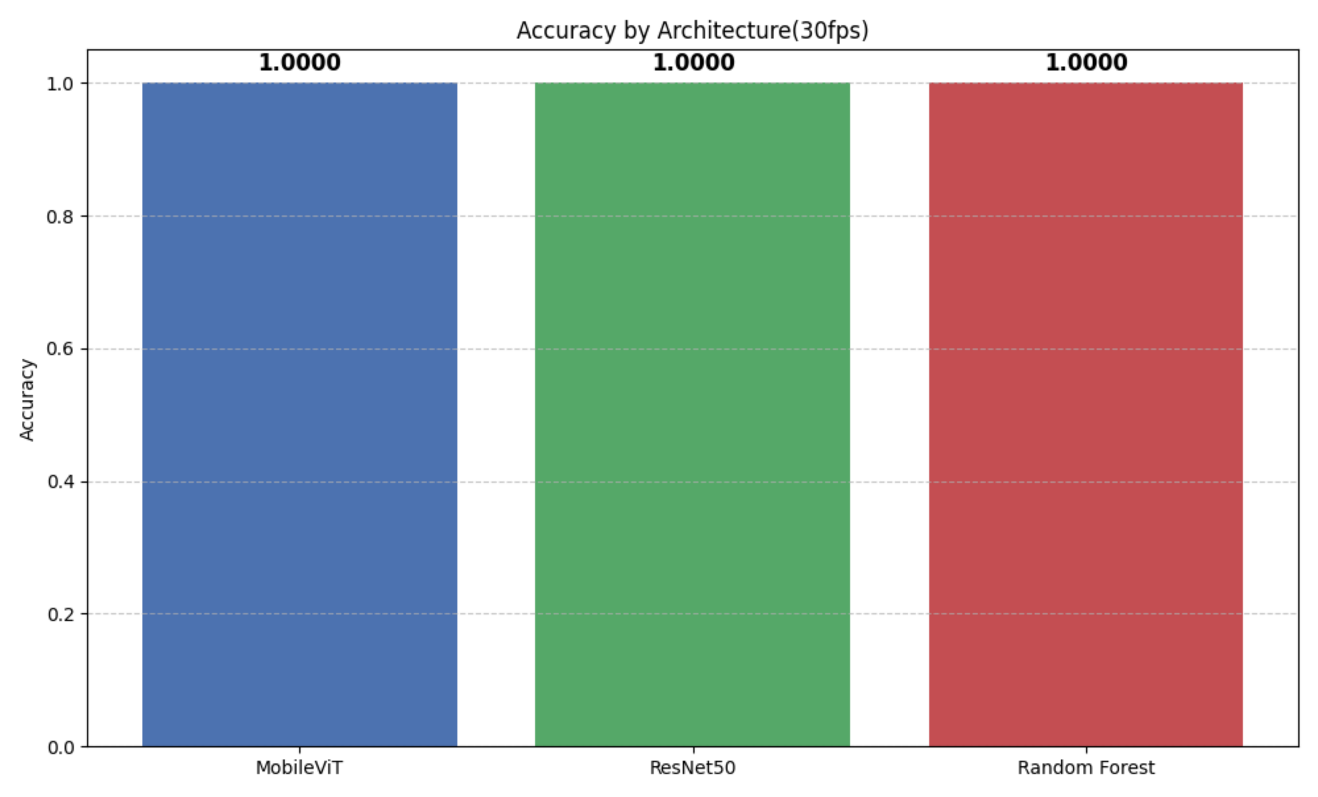
Loss Functions and Metrics

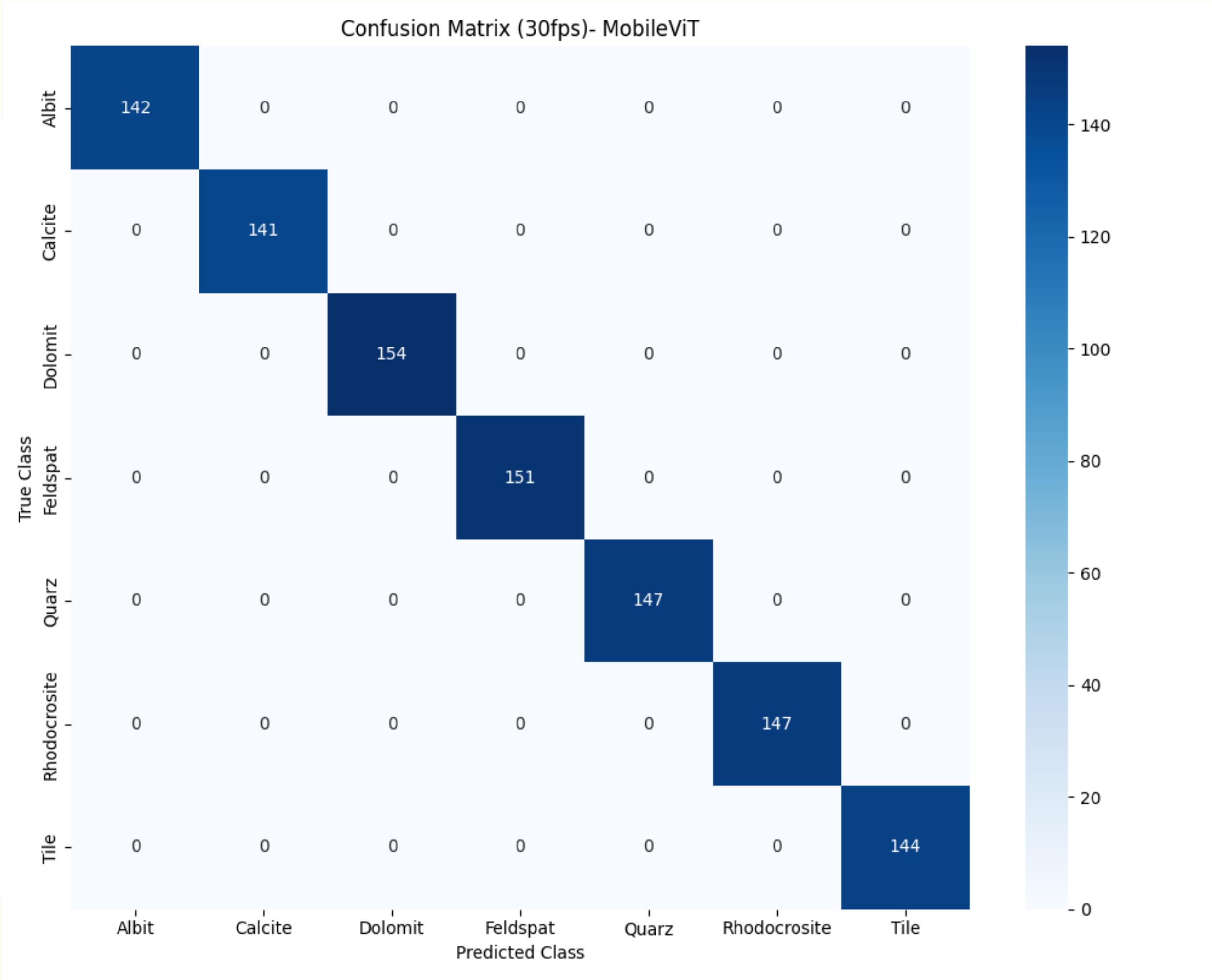
Cross-entropy loss guided deep learning while random forest models used impurity measures like Gini index for evaluation.

Results

Data Type	FPS	Model	Accuracy	Training Time	Memory Usage
Image	**30**	**MobileViT-XS**	**100%**	**Fast**	**Low**
Image	30	ResNet50	100%	Moderate	High
Image	30	Random Forest	100%	Moderate	High
Image	**1**	**MobileViT-XS**	**100%**	**Fast**	**Low**
Image	1	ResNet50	100%	Moderate	High
Image	1	Random Forest	100%	Moderate	High
Profile	**30**	**Random Forest**	**~96.3%**	**Instant**	**Very Low**
Profile	**30**	**MLP**	**~95.7%**	**Very Fast**	**Very Low**
Profile	30	1D-CNN	~85.4%	Very Fast	Very Low
Profile	**1**	**Random Forest**	**~99.9%**	**Instant**	**Very Low**
Profile	1	**MLP**	**~99.7%**	**Very Fast**	**Very Low**
Profile	1	1D-CNN	~99.5%	Very Fast	Very Low

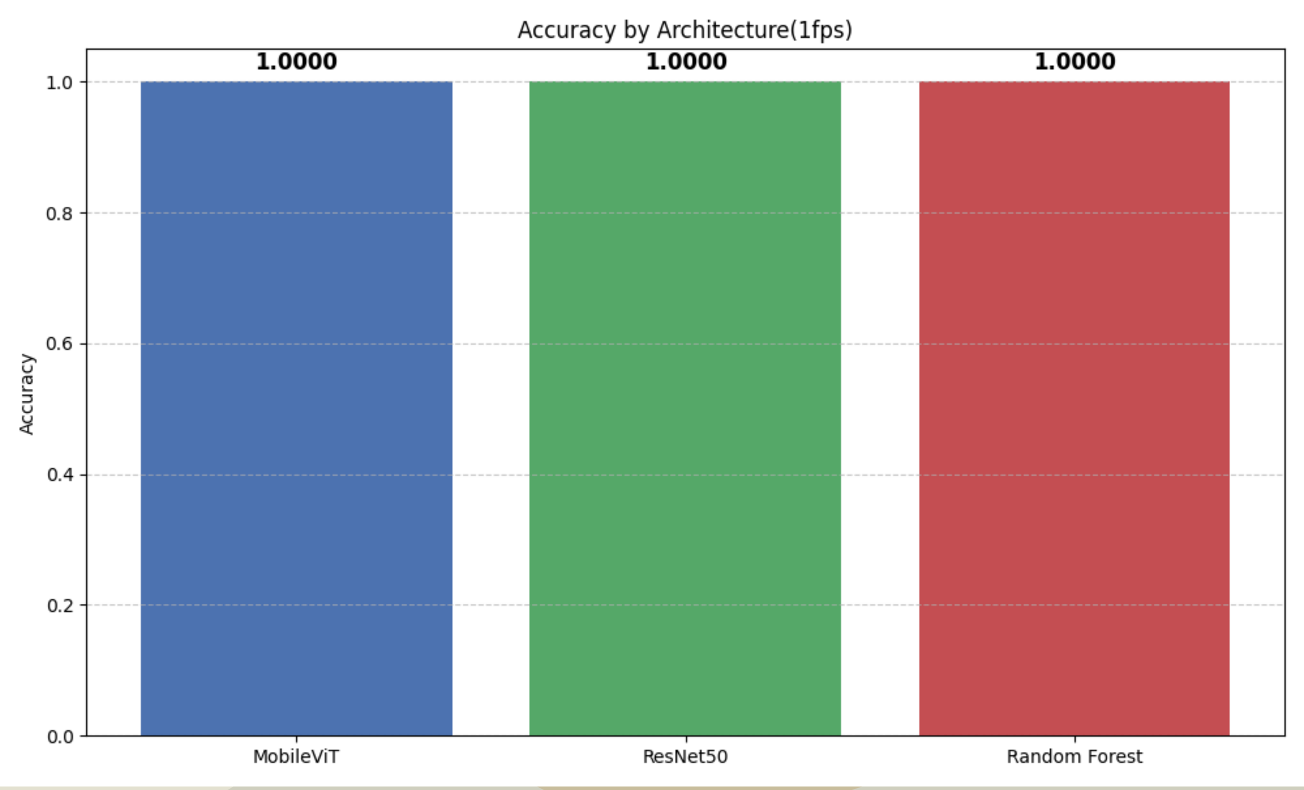
Visuals (Images 30 fps)

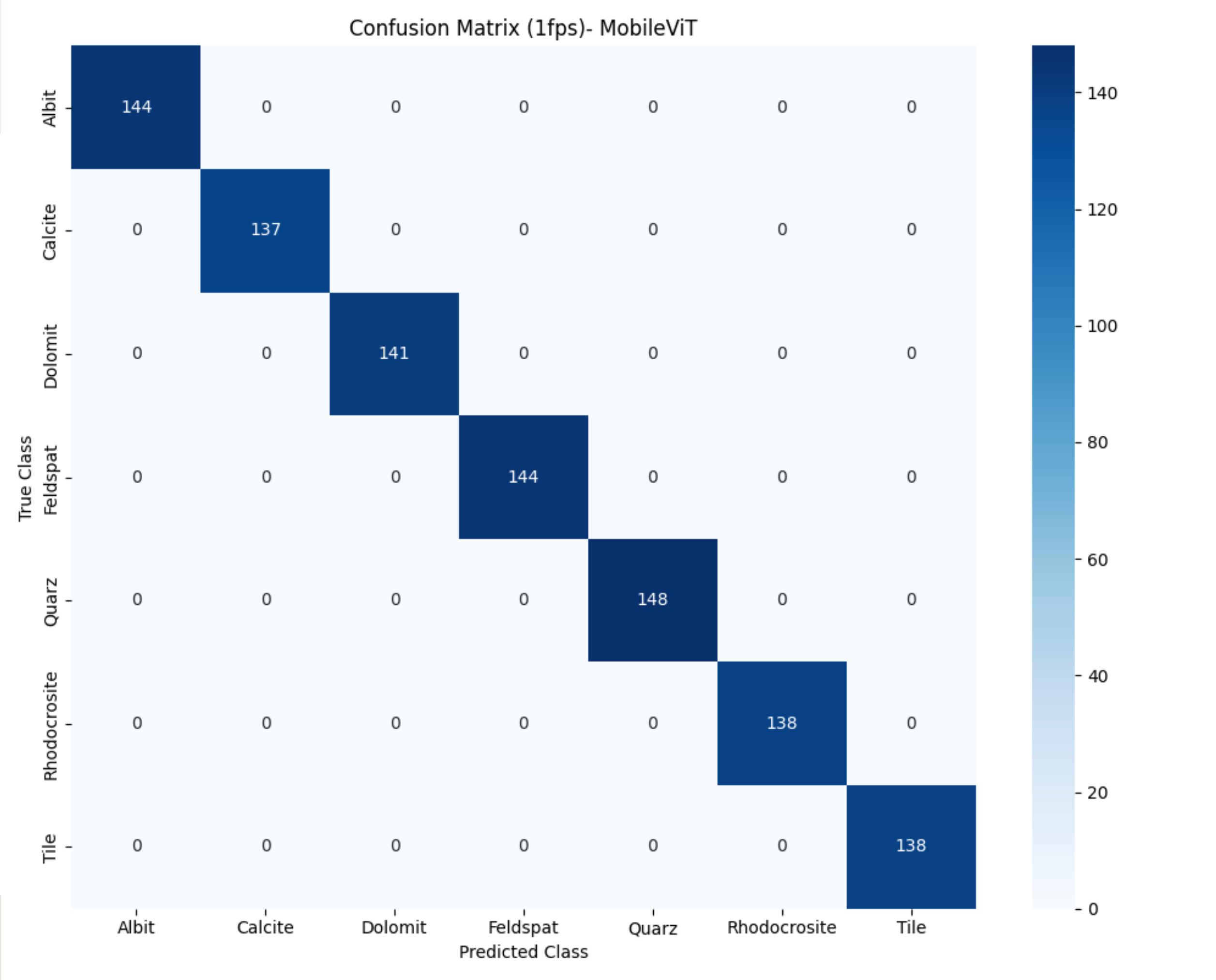




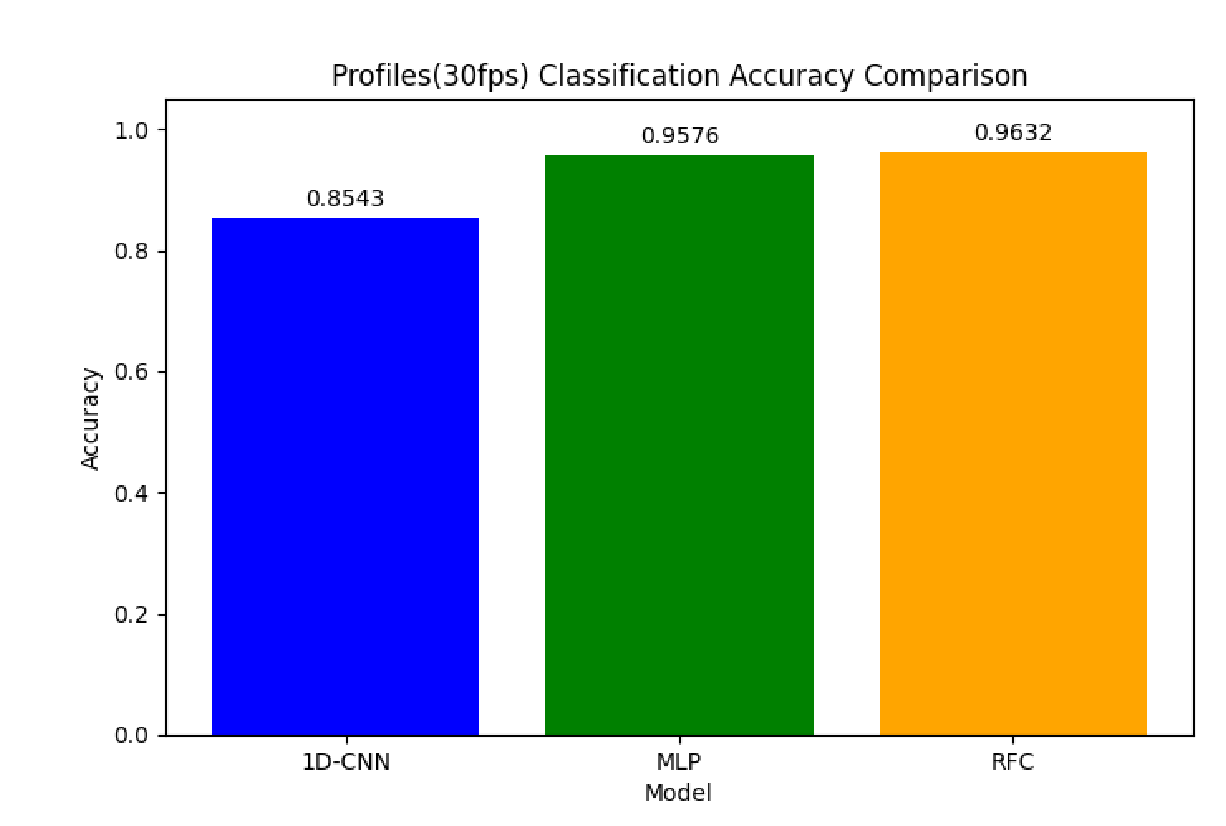
1/13/2026

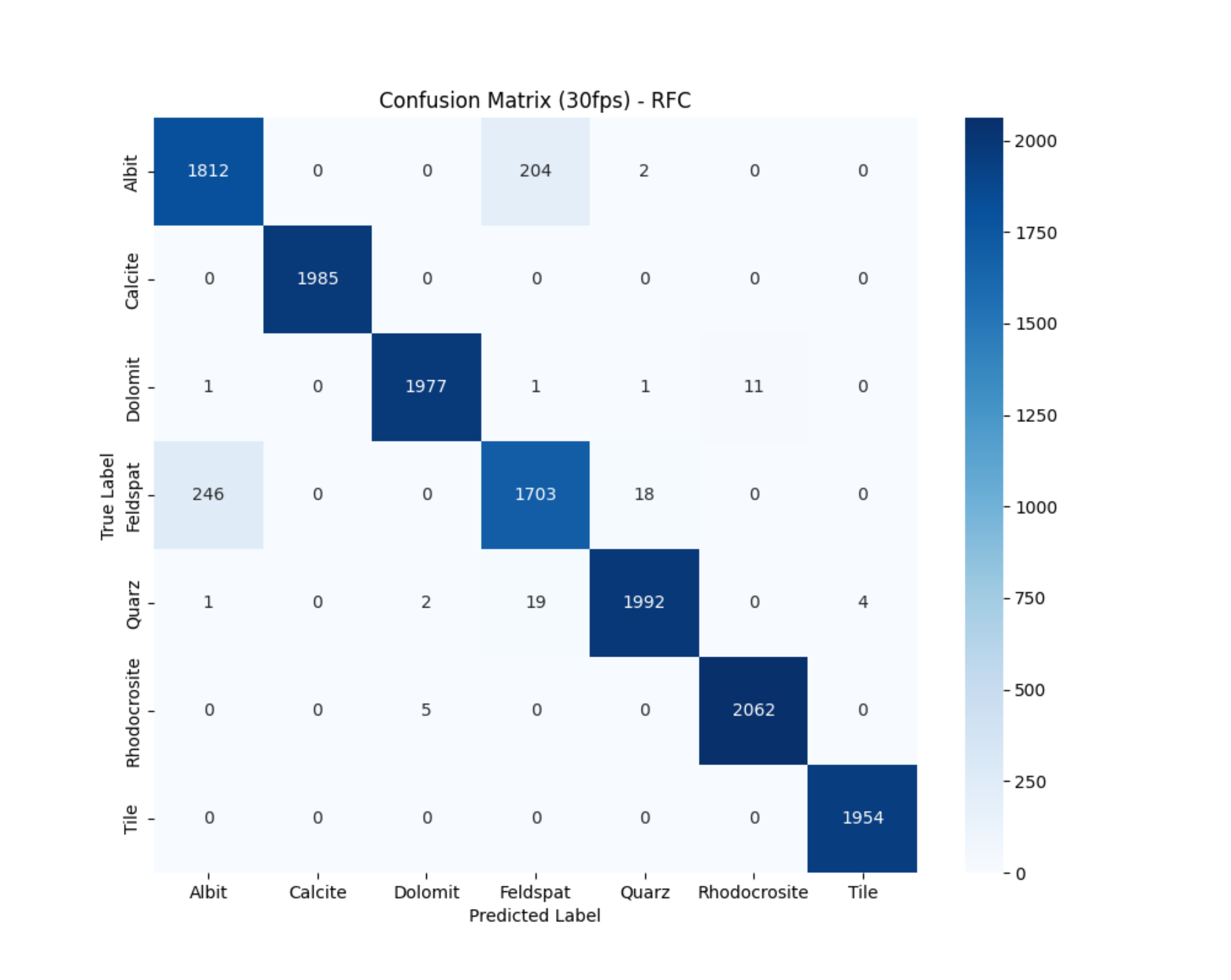
Visuals (Images 1 fps)



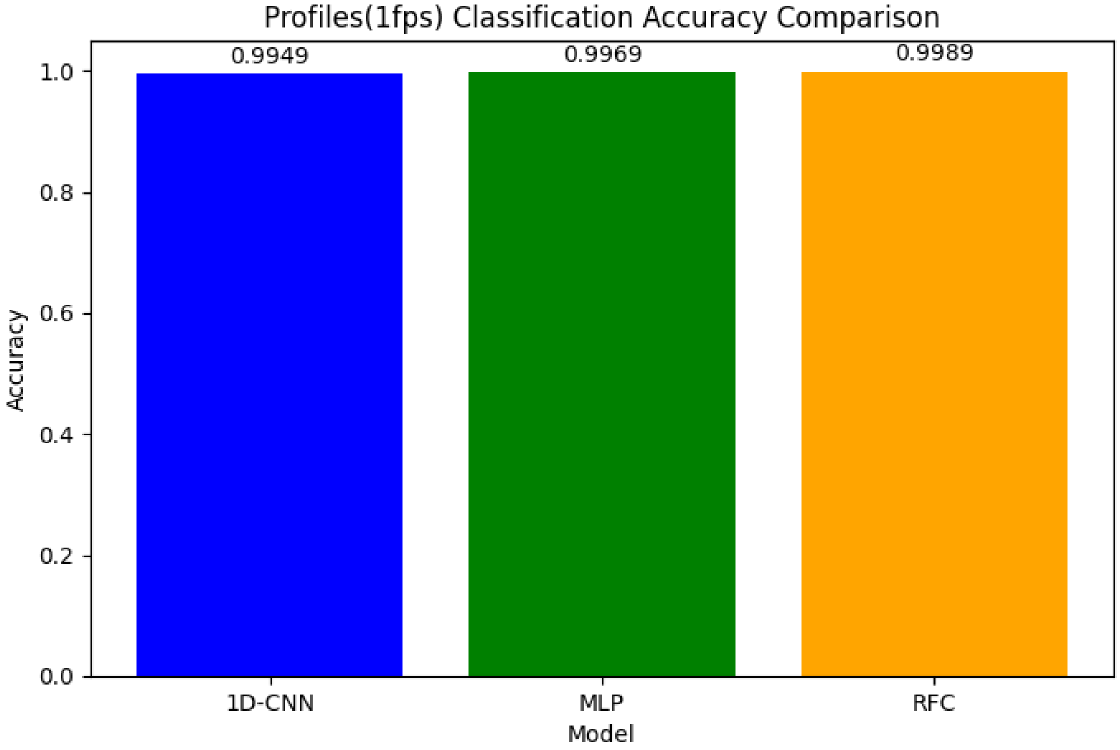


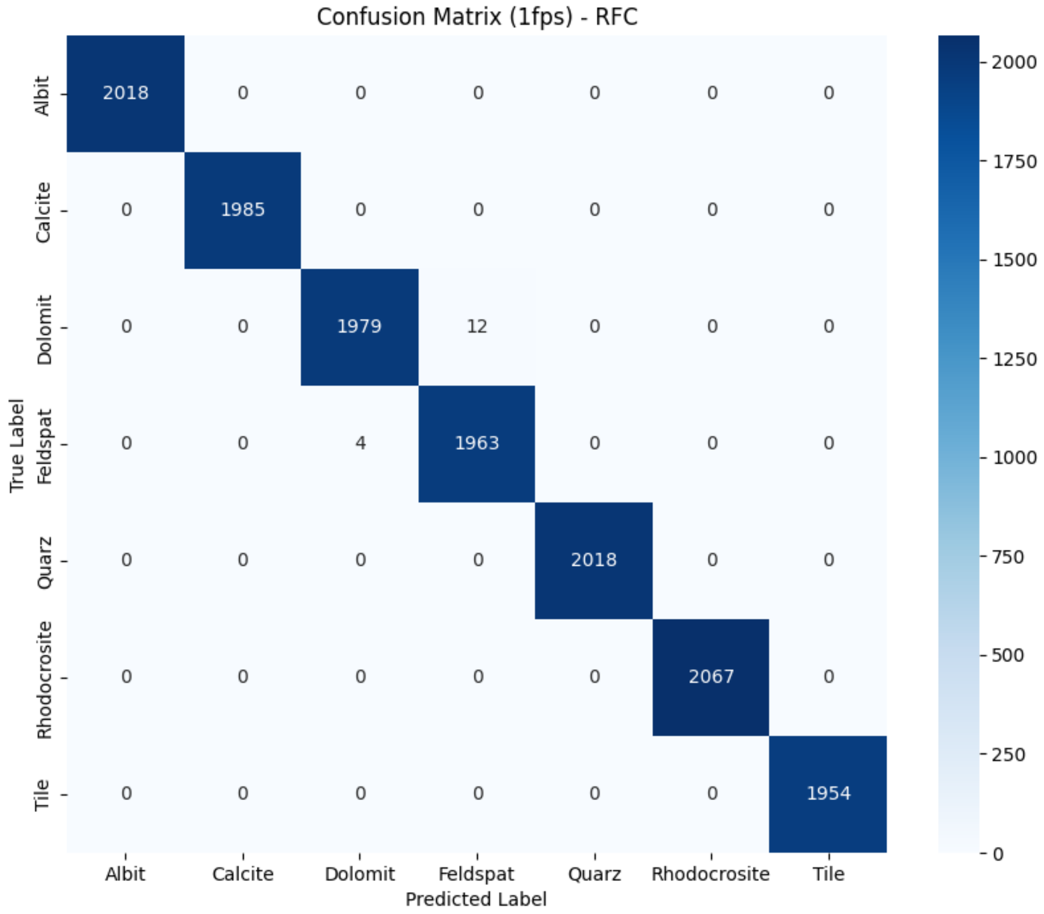
Visuals (Profiles 30 fps)



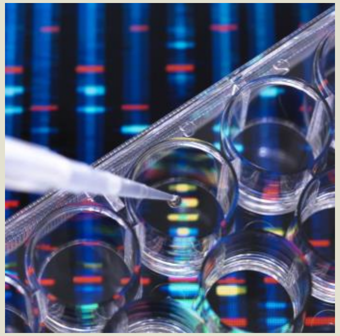


Visuals (Profiles 1 fps)



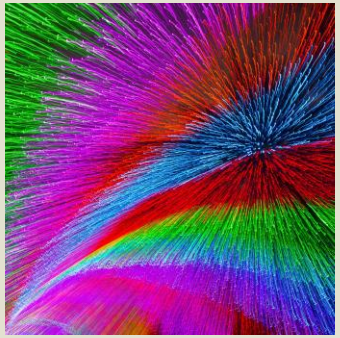


Key Takeaways and Future Directions



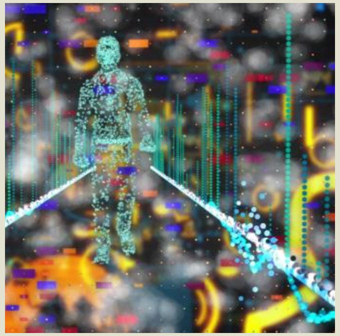
AI-driven Mineral Classification

AI models like MobileViT-XS provide high accuracy and robustness in classifying minerals using spectral images.



Spectral Profiles Advantages

Spectral profiles offer faster processing and lower resource use, suitable for lightweight mineral classification tasks.



Future Research Directions

Hybrid models combining images and profiles and optimizing edge device inference could enhance mineral identification.