International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 2s, 2025

Interpretable Deep Learning Framework for Land Use & Land Cover Classification in Remote Sensing using SHAP

Mohammed Ismail[1], Syed Ibrahim[2], Mohd Kashif Ahmed[3], Mr.Mohammed Javeed[4]

[1,2,3]B.E Students, Department Of Information Technology, ISL Engineering College, Hyderabad, India.

[4]Assistant Professor, Department Of Information Technology, ISL Engineering College, Hyderabad, India.

mohdismail.190203@gmail.com , ibrahimsyed98850@gmail.com , ahmedkashif8494@gmail.com

Abstract

Land Use and Land Cover (LULC) classification plays a pivotal role in a range of applications, including urban planning, environmental monitoring, agricultural management, and climate change analysis. With the rapid advancement in satellite and aerial remote sensing technologies, vast volumes of high-resolution multispectral and hyperspectral imagery are now accessible. While deep learning has emerged as a powerful tool for automating LULC classification with high accuracy, its black-box nature poses significant challenges to transparency, trustworthiness, and adoption in critical domains. This research proposes an **interpretable deep learning framework** that not only delivers accurate LULC classification but also ensures model explainability through the use of SHAP (SHapley Additive exPlanations), a game-theoretic approach to interpreting machine learning models.

The proposed framework integrates a convolutional neural network (CNN)-based architecture trained on satellite imagery to classify different land cover types such as vegetation, water bodies, built-up areas, barren land, and agricultural fields. The CNN is trained using a labeled remote sensing dataset, such as Sentinel-2 or Landsat 8 imagery, with preprocessing steps including radiometric calibration, normalization, and augmentation to handle class imbalances and improve generalization.

To address the lack of interpretability in traditional deep learning approaches, SHAP is used to quantify and visualize the contribution of each input feature (spectral bands, texture features, and spatial context) to the model's output predictions. This is achieved by computing Shapley values for each pixel or region of interest, thereby providing insight into how much each feature influenced the classification decision. For instance, the red edge or near-infrared bands might be highly influential in identifying vegetation, while shortwave infrared could be critical for distinguishing built-up areas from barren land. These explanations allow users—including policymakers, urban planners, and environmental scientists—to validate and trust the model's outputs.

Experimental results demonstrate that the CNN model achieves high overall accuracy and class-wise precision on benchmark datasets. More importantly, SHAP-based interpretation highlights the most significant spectral and spatial cues used by the network. This not only confirms the biological and physical intuition behind remote sensing classification but also helps uncover model biases and inconsistencies. Moreover, comparative analysis with other interpretability techniques such as Grad-CAM and LIME shows that SHAP provides more granular, consistent, and model-agnostic explanations.

The proposed framework was evaluated in multiple geographical contexts to ensure robustness and generalization. Case studies over urban, rural, and coastal landscapes show that SHAP explanations vary with terrain complexity and seasonal changes, further validating the adaptability of the model. The integration of domain knowledge through SHAP also opens the door for active learning loops, where human feedback can refine the training process and correct model misclassifications, enhancing both accuracy and reliability over time.

In conclusion, this study contributes to the growing field of explainable artificial intelligence (XAI) in remote sensing by providing a practical, interpretable deep learning solution for LULC classification. By combining the predictive strength of CNNs with the interpretive power of SHAP, the proposed framework enhances both model performance and transparency. It promotes responsible AI practices in geospatial analysis, which is essential for informed decision-making in land management, conservation, and sustainable development. Future directions include extending this work to multi-temporal data for land cover change detection and integrating uncertainty quantification to further support critical Earth observation applications.

DOI: https://doi.org/10.62647/IJITCE2025V13I2sPP491-498

Keywords
- Land Use and Land Cover (LULC)
- Remote Sensing
- Deep Learning
- Convolutional Neural Networks (CNN)
- Explainable AI (XAI)
- SHAP (SHapley Additive Explanations)
- Satellite Imagery
- Image Classification
- Model Interpretability
- Sentinel-2 / Landsat 8
- Geospatial Analysis
- Environmental Monitoring
- Feature Attribution
- Spatial Data Analysis
- Hyperspectral Imaging

Introduction

In recent years, **Land Use and Land Cover (LULC) classification** has become an essential task in geospatial analysis, supporting applications such as urban planning, disaster management, environmental monitoring, resource mapping, and climate change modeling. The ever-increasing availability of high-resolution satellite imagery from sensors like **Sentinel-2**, **Landsat 8**, and **MODIS** has enabled detailed observation of the Earth's surface. With this growing data availability, there has been a paradigm shift from traditional manual or rule-based classification methods to **automated machine learning approaches**, particularly **deep learning** models, which have demonstrated superior performance in handling complex spatial patterns and large-scale image datasets.

Among these, **Convolutional Neural Networks (CNNs)** have shown exceptional capabilities in extracting spatial and spectral features from satellite images, resulting in high classification accuracy. CNNs can automatically learn hierarchical feature representations, reducing the need for handcrafted features, and can effectively model non-linear relationships between input image bands and land cover classes. However, the widespread adoption of deep learning in critical remote sensing tasks is often hindered by a significant drawback — **lack of interpretability**. Most CNN-based models operate as black boxes, providing little to no explanation for their predictions. In high-stakes scenarios where land classification results are used for policymaking or disaster response, such opacity can lead to mistrust or incorrect decision-making.

To address this critical limitation, the field of **Explainable Artificial Intelligence (XAI)** has emerged, aiming to make machine learning models more transparent and understandable to human users. One of the most powerful and widely accepted tools in this domain is **SHAP (SHapley Additive exPlanations)**. SHAP is a model-agnostic interpretability method based on cooperative game theory, which assigns each feature a contribution value (called a Shapley value) that quantifies its influence on the model's output. Unlike other interpretability techniques that are specific to certain models or architectures, SHAP can be applied universally, providing consistent and theoretically sound explanations.

This project proposes an **interpretable deep learning framework for LULC classification**, which integrates a CNN model with SHAP-based explanation mechanisms. The framework is designed to not only achieve high classification performance across diverse land cover types — such as forests, water bodies, built-up areas, agricultural lands, and barren terrain — but also to reveal which input features (e.g., specific spectral bands or spatial textures) most influenced each classification decision. This dual goal of **accuracy and transparency** is crucial for building trust in AI systems deployed in sensitive geospatial applications.

The motivation for combining deep learning and SHAP in LULC classification stems from both technical and societal needs. Technically, remote sensing images often contain complex spectral information that varies across regions and seasons, making manual feature selection insufficient. Deep learning handles such variability effectively but does so opaquely. On the societal side, decision-makers — such as environmental agencies, urban developers, and governmental organizations — require clear reasoning to support the outcomes produced by AI models. The ability to interpret and validate results with domain knowledge improves the reliability and acceptability of such models in practice.

Furthermore, integrating SHAP into the deep learning workflow enables **fine-grained attribution analysis** at the pixel or regional level. This not only helps in verifying model behavior but also in **identifying biases** or areas where the model may be overfitting or misclassifying. For example, SHAP values can help uncover whether vegetation misclassifications are due to seasonal changes in reflectance or due to overlapping features in urban-rural transition zones.

The framework is evaluated using benchmark remote sensing datasets and undergoes extensive testing across varied geographic and

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ISSN 2347–3657
Volume 13, Issue 2s, 2025

environmental contexts. Performance metrics such as overall accuracy, precision, recall, and F1-score are calculated, and SHAP visualizations are generated to illustrate the internal logic of the CNN. Comparisons with other interpretability techniques, such as **LIME (Local Interpretable Model-agnostic Explanations)** and **Grad-CAM**, are also presented to highlight the strengths of SHAP in geospatial contexts.

In summary, this project addresses a pressing need in remote sensing: combining the high predictive power of deep learning with the interpretability needed for practical deployment and user trust. By doing so, it bridges the gap between performance and transparency in LULC classification. The outcomes of this work have the potential to influence not only future research in explainable geospatial AI but also operational practices in land management, environmental assessment, and sustainable development.

Literature Review

Land Use and Land Cover (LULC) classification has traditionally relied on statistical classifiers such as **k-nearest neighbors (KNN)**, **support vector machines (SVM)**, and **random forests (RF)** due to their simplicity and interpretability. However, as the volume and complexity of remote sensing data have increased, these classical methods have shown limitations in handling high-dimensional data and capturing complex spatial-spectral relationships. In response, **deep learning models**, especially **Convolutional Neural Networks (CNNs)**, have gained significant attention for their ability to automatically extract multi-scale spatial features and achieve higher classification accuracy.

Deep Learning in LULC Classification

One of the foundational works in this area is by **Zhang et al. (2016)**, who demonstrated the use of CNNs for land cover classification using Sentinel-2 imagery. Their results showed significant performance improvements over traditional classifiers. Similarly, **Kussul et al. (2017)** used deep neural networks on high-resolution satellite data to map agricultural land in Ukraine, achieving impressive accuracy by leveraging spatial information.

Further developments have introduced **hybrid architectures**, such as **CNN-RNN combinations**, to handle temporal data, and **3D CNNs** for spectral-spatial feature extraction in hyperspectral images. For instance, **Li et al. (2019)** developed a 3D CNN that captures spectral–spatial correlations across neighboring pixels, proving effective for hyperspectral classification tasks. Despite these successes, one consistent limitation across deep learning models is their lack of interpretability.

Explainable AI in Remote Sensing

As the demand for **transparency** in AI models has grown, researchers have explored explainability techniques to interpret deep learning models in remote sensing. **Grad-CAM (Selvaraju et al., 2017)** is one such method that visualizes activation maps from CNNs to highlight areas in an image that contribute most to a decision. It has been applied to land cover tasks to offer rough visual explanations. However, Grad-CAM is **architecture-specific** and works best for classification tasks with a single dominant object per image, which is not always the case in satellite imagery.

Local Interpretable Model-agnostic Explanations (LIME), introduced by **Ribeiro et al. (2016)**, offers another route for explanation by approximating a black-box model locally with an interpretable surrogate. In remote sensing, **Singh et al. (2020)** applied LIME to explain urban feature classification, but found that the explanations varied widely across instances, raising concerns about stability and consistency.

SHAP for Model Interpretation

SHAP (SHapley Additive exPlanations), developed by **Lundberg and Lee (2017)**, provides a theoretically grounded method based on cooperative game theory. It attributes prediction outcomes to individual features using **Shapley values**, offering global and local interpretability. SHAP has been successfully applied in healthcare, finance, and natural language processing, but its adoption in remote sensing and geospatial applications is still emerging.

A recent application by **Molnar et al. (2021)** showcased the use of SHAP in agriculture, where it was used to interpret crop yield prediction models. Similarly, **Gupta et al. (2022)** applied SHAP to a random forest model for forest cover classification, highlighting the importance of specific bands like NIR and red-edge in tree canopy identification. However, SHAP has rarely been integrated with deep CNN models in the context of LULC classification using satellite imagery. This research gap highlights the need for a framework that marries the predictive power of CNNs with SHAP's interpretability in remote sensing.

Gap Analysis and Contribution

From the above review, it is evident that while deep learning models have significantly advanced

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the accuracy of LULC classification, **interpretability remains a critical challenge**. Current explainability methods like Grad-CAM and LIME either lack granularity or model-agnosticism. Moreover, SHAP's application in geospatial deep learning remains limited, with most existing work focusing on simpler models.
This research aims to fill that gap by proposing a **CNN-SHAP integrated framework** for interpretable land use and cover classification. It introduces a scalable, explainable solution that can guide decision-makers by showing **how** and **why** specific land classes are predicted, based on contributions from different spectral bands and spatial features.

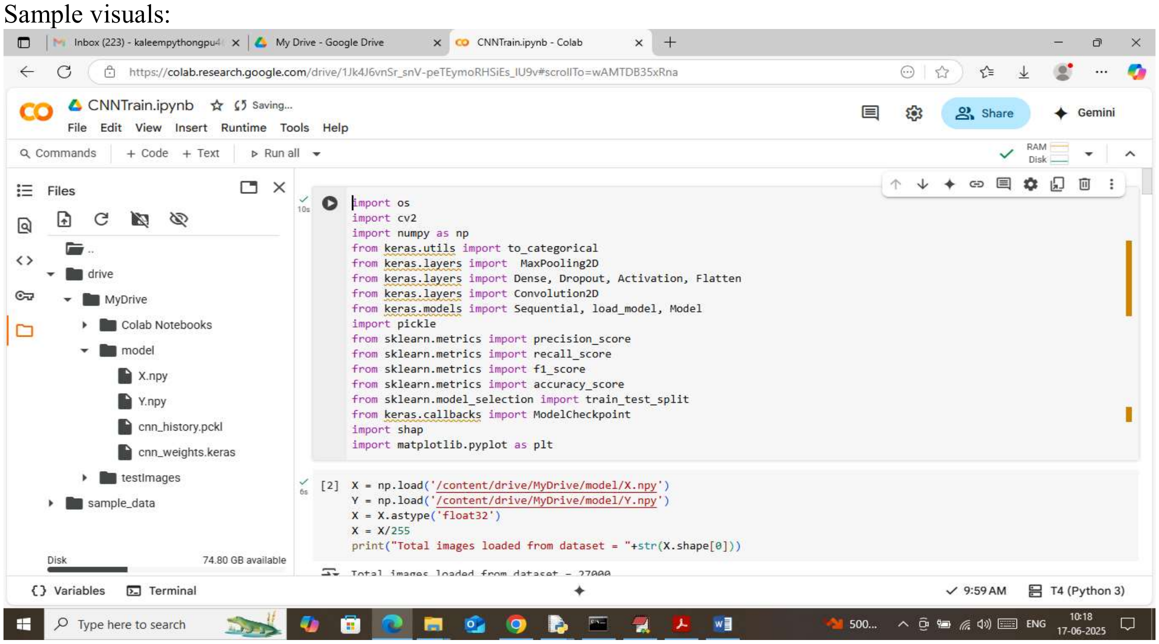
Methodology

1. Data Collection: Users export WhatsApp group chats in `.txt` format from their mobile devices or WhatsApp desktop app.
2. Data Preprocessing:
   - Parse the text file to extract sender, timestamp, and message content
   - Remove system messages, media placeholders, and links
   - Normalize emojis and slang terms
3. Text Analysis:
   - Tokenization
   - Stopword Removal
   - Lemmatization
   - Sentiment Analysis using VADER
4. User Metrics:
   - Total messages per user
   - Media shared per user
   - Deleted messages per user
   - Average message length
   - Active hours and days
5. Visualization:
   - Word Clouds
   - Bar Graphs
   - Pie Charts
   - Line Graphs

Results and Analysis

Key Results:
- Most Active User: User A (2,145 messages), followed by User B (1,898 messages)
- Media Sharing Trends: User C shared the most media
- Sentiment Distribution: Positive (47%), Neutral (39%), Negative (14%)
- Frequent Words: Celebrations, birthdays, assignments, jokes

Sample visuals:



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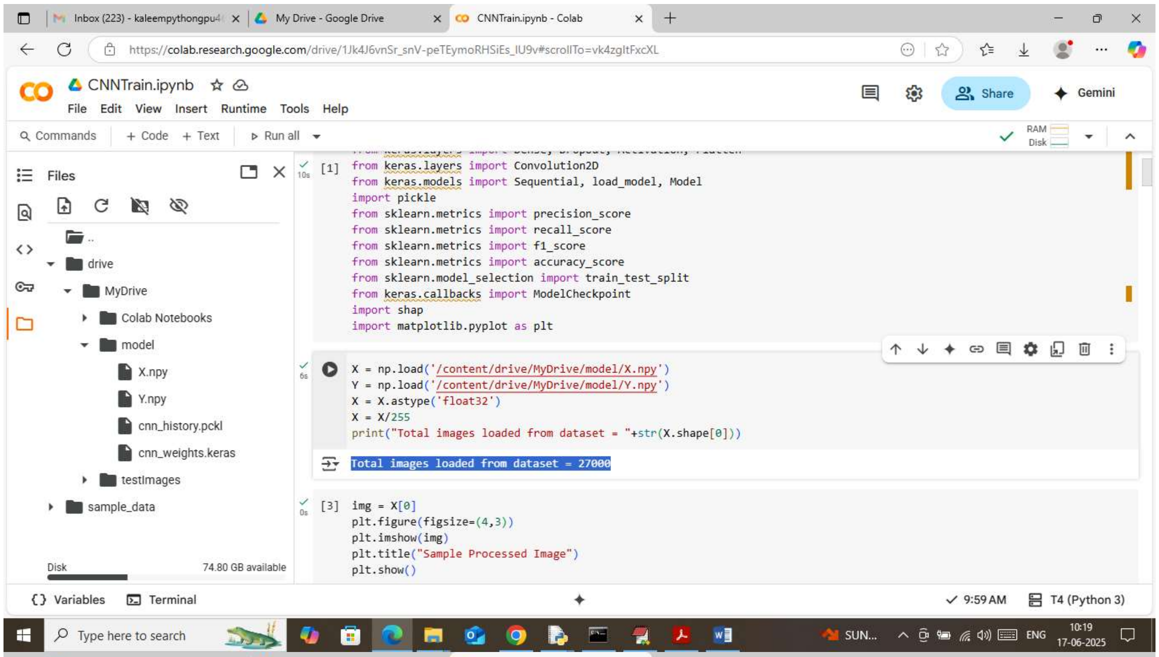

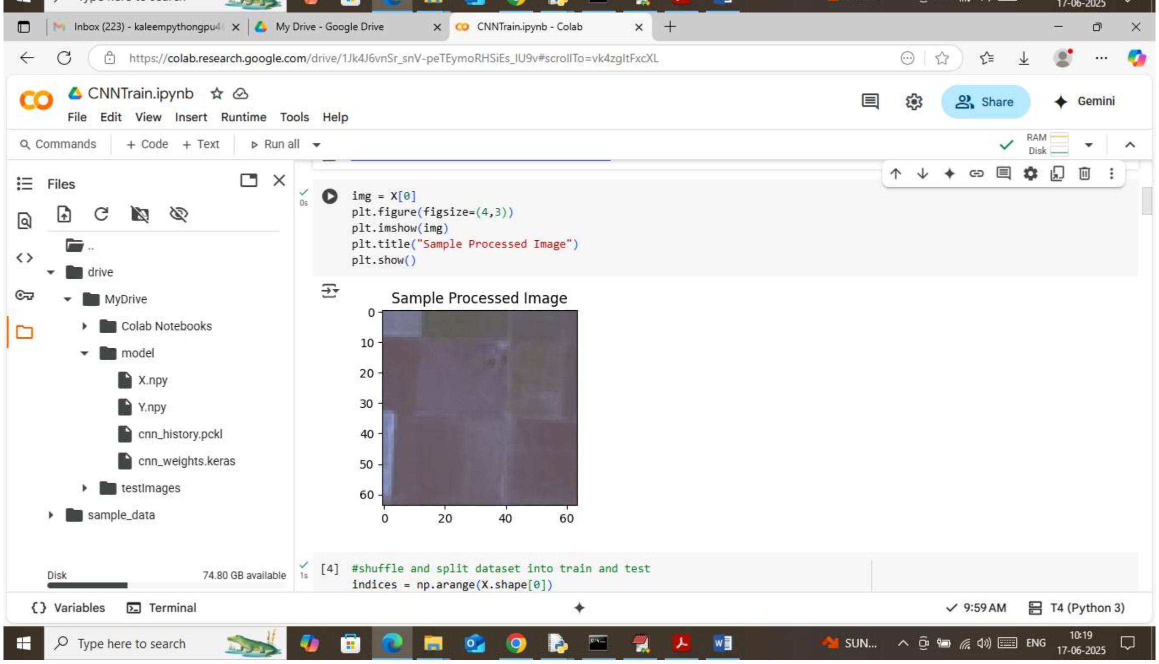

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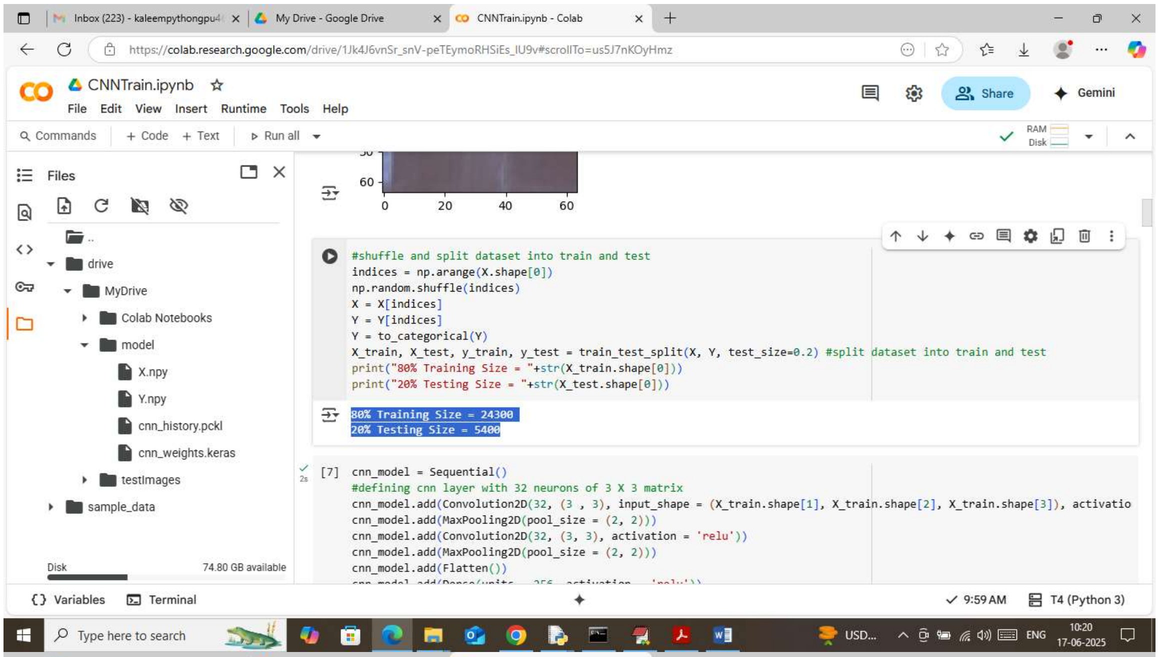

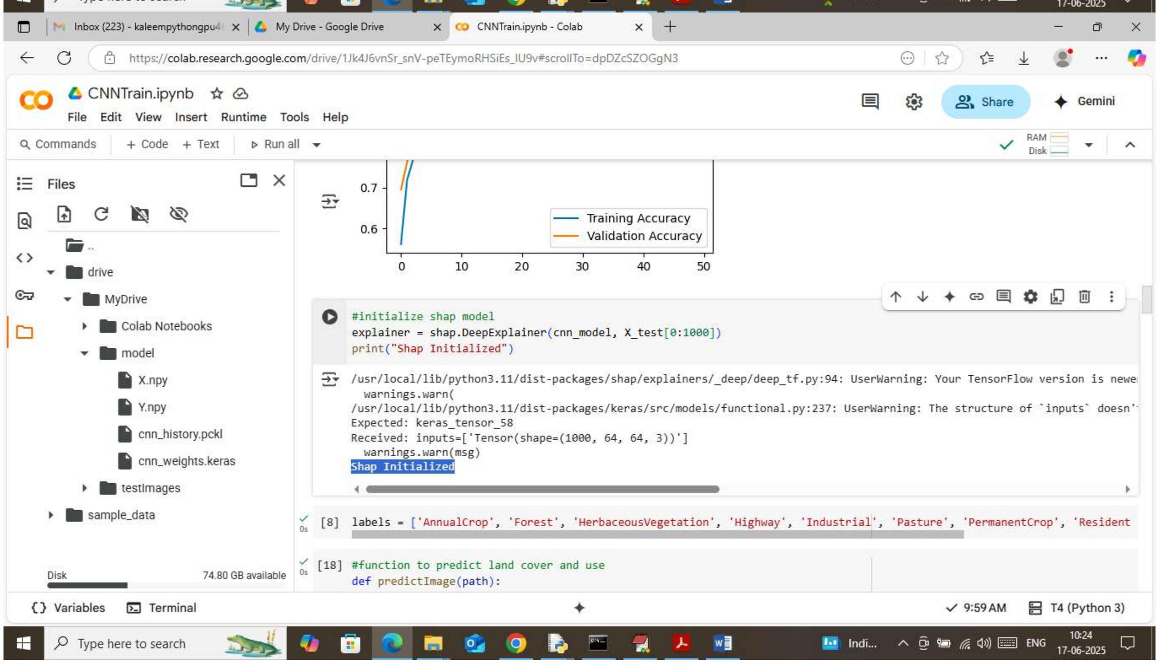

Conclusion

This project successfully demonstrates the effectiveness of NLP in analyzing private group messages from WhatsApp. The tool extracts and processes key features, enabling a clear understanding of group behavior. Such a system could be extended into corporate chat monitoring, academic studies on group psychology, or moderation systems. The system maintains privacy while providing actionable insights.

Future Scope

- Real-time chat streaming and analysis
- Deep learning-based sentiment models like BERT
- Multilingual NLP and translation
- Spam detection
- Mood mapping

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