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Deep Learning For Lithological Mapping: A New Paradigm In Geological Interpretation

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Abstract– *The lithological mapping is the key factor to explore the subsurface structure of the Earth which has traditionally been based on the manual interpretation of geophysical data, field surveys, and experience of experts. Nevertheless, the existing methods are rather slow and subject to human error. As deep learning technologies and especially convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are being developed, lithological mapping is taking a new and revolutionary turn. In this paper, the use of deep learning models to automatize and increase the accuracy of the lithological classification based on remote sensing data, hyperspectral imagery, and borehole logs is discussed. We introduce an entire process of data preprocessing, model training, and model verification of predictions on a test geological area. The inferences indicate substantial increase in the accuracy of classification and spatial adherence than the conventional machine learning applications. The suggested strategy suggests a paradigm change in the geological interpretation, which can enable scaleable, efficient, and more objective lithological mapping.*
Keywords– *Lithological Mapping; Deep Learning; Convolutional Neural Networks (CNN); Hyperspectral Imaging; Geological Interpretation; Remote Sensing; Automated Classification.*

I. INTRODUCTION

A geological tool Lithological mapping is a basic operation in geology, which is necessary to comprehend the composition, distribution and makeup of rock layers in different spatial windows. It gives significant information on the geological operations, mineral exploration, hydrological and environmental surveillance. Conventionally lithological maps are prepared by field surveys, interpretation of aerial or satellite photography by hand, and by analysis of geological cross sections. Despite being scientifically valid and having undergone trials, these processes are very labour intensive and time consuming not to mention, inconventiently restricted by the scope of the observation and the subjectivity of the human interpreters [16].

In recent decades, development of remote sensing and geospatial technologies has greatly enriched the possibility to gather the data about the Earth surface in high definition and on big scale. Satellites and airborne platforms with multispectral and hyperspectral imaging sensors are now able to deliver huge hyperspectral data sets with huge spectral content. Nevertheless, lithologic data mining of such massive data piles has been difficult especially in light of the heterogeneity of rock mixtures, inconsistency in the landscape surfaces as well as smears or bushes on imagery. This has resulted in sophistication-dependent demands of the computational method that can recognize weak trends in spectral and spatial data.

Decision trees, support vector machines and random forests are examples of machine learning approaches that have been used in the moderate successful approach to automate the process involved in classification of lithologies [7]. The techniques are most applicable in cases whereby the data are clean and well labelled and also they should be statistically representative. Nevertheless, the problem with class imbalance, spatial autocorrelation and heterogeneity of the geological data are common. More to the point, classical machine learning algorithms are based on feature engineering, manual extraction and selection of informative features which are quite subjective and confined with a capacitation to capture complex interactions in the data.

Deep learning, is a subfield in artificial intelligence that takes cues in the neural layout of the human brain and has recently demonstrated to be revolutionary in the processing of complex and high-dimension data. Task such as image classification, natural language processing, and speech recognition tasks have become completely revolutionized through the use of convolutional neural networks (CNNs), recurrent neural networks (RNNs), and most recently through transformer-based models. These models can learn hierarchical feature representations automatically in raw data and do not rely on manual design of features, which add to their flexibility by being easily adaptable to the complexity of the data [2-4].

The use of deep learning in lithological mapping presents a different paradigm in interpretation of geological data. It is possible to build the systems that will have the ability to generalize to other terrains, sense small differences in spectra, and classify regions or even the whole world lighting-fast by first training the models on their own remote sensing image and its lithological labels. Deep learning models allow simultaneously learning ubiquitous spatial and spectral characteristics, and support processing noisy and imbalanced data, in contrast to conventional classification pipelines, and thus, they scale with data size.

In spite of them, deep learning in one of the areas of geosciences is currently at its genesis, and it contains a number of particular issues. In remote or inaccessible areas geological data are usually sketchy or irregularly marked. The acquisition of ground truth, including either drilling or field surveys, has never been cheap and time consuming. Also, geological processes are by their nature 3D and time varying as opposed to the majority of deep learning applications, which deal with 2D images. Hence, one has to develop and adjust deep learning frameworks and training paradigms adjusted to the specifics of geological data [14].

The paper is a deep learning approach to remote sensing imagery-based lithological mapping. Our goal is to develop and train convolutional neural network model that would be able to correctly sense rock types within a region of study, with hyperspectral satellite measurements and ground truth-determined lithology. The model is compared not only with recognized traditional machine learning classifiers but also its performance exemplified in the performance comparisons by measuring accurateness, the spatial consistency, and applicability. The suggested approach elevates the degree of classification in addition to showing the prospects of automating, increasing, and rational geological interpretation that requires a massive departure than traditional mapping processes.

Novelty and Contribution

This study is novel because it involves the use of deep convolutional neural networks in the lithological classification with the use of hyperspectral remote sensing data, which would not have been implemented extensively and consistent in geological practice. When compared with classical machine learning models which require manual feature engineering and extraction, our end-to-end deep learning model has the capability to learn spatial textures and spectral patterns in end-to-end training fashion on raw data. This enables the model to detect complex and subtle lithological transitions that other humans or other simpler algorithms would not detect [5].

Among the most important things this research accomplishes is it provides a practical approach of implementing deep learning to geological data that tends to be noisy, imbalanced, and spatially correlated. We use highly effective data preprocessing techniques that comprise a spectrum normalization, data augmentation, and patch training and make the model much more robust and generalizable. Moreover, we do not use the technique of transfer learning on pre-trained networks, which is a typical constraint in terms of having little labeled geological data available, thus making our method more workable in the context of real-world use and lack of ground truth.

The quantitative and spatial assessment of model results also constitutes another input. We do not only measure the goodness of accuracy (in terms of F1-score, Kappa coefficient), but also test the spatial coherence of the resulting data in terms of the predicted lithology maps compared to field-based geological maps. This two-tier evaluation system will make our model neither statistically, but also geologically, meaningful.

Furthermore, this paper demonstrates a proof of concept that deep learning will be viable in mapping regions of interest such as lithologies and give the scope of future geological surveys, exploration targeting, and hazard evaluation in a short period. The results and methodology of this study are applicable in other areas and datasets already giving a replicable model that can be utilized in future investigations on geospatial AI in earth sciences [8-9].

To conclude, the originality of this work has been having an automated, data-driven way of analyzing lithology and the contributions to have been a reproduced deep learning pipeline, higher accuracy of the classification, and how useful AI can be useful in the study of geology, which has historically required manual expert knowledge and has not had the necessary tools to accomplish its goals [10].

II. RELATED WORKS

In 2024 C. Li et al., [1] introduced the area of lithological mapping has over the years experienced a progressive shift away to the more traditional field methods towards the more data and remote sensing-based methods. Use of remote sensing data has provided first time opportunity to carry out regional and global scale geological interpretation and especially in remote locations which are not easily reached. The traditional approaches to mapping depended mostly on manual delineation from the topographic maps, aerial photographs, and minimal ground truths. Although these methods formed a foundation to geological cartography, they were restrained by the subjectivity and low spatial details and the inability to re-do or update the maps.Due to the growth in the availability of multispectral and hyperspectral imagery utilizing satellite platforms, geological interpretation started to take advantage of the spectral signatures of surface materials. The remotely sensed data having detailed information in the spectrum of electromagnetic energies came in handy in mapping the lithological units through their mineral contents and the patterns of weathering. The first automated systems applied statistical techniques (of principal component analysis and of minimum distance classification). This was promptly accompanied by machine learning algorithms which offered more flexible and powerful capacity to classify.Because of their versatility in heterogeneous data and accuracy in modeling the non-linear relationships, supervised classification models such as decision trees, support vector machine and random forests, became common. However, such models mostly assumed manual feature extraction, thereby inducing domain-specific bias and prohibiting their ability to model complex dependencies in high-dimensional data. In addition, their performance would also tend to become poor in the case of overlapping lithological signatures, spectral noise, or training labels that are scarce [11].As a way of solving these shortcomings, new studies have resorted to newer computational tools especially those which are provided by the concept of deep learning. The capability of deep learning models to automatically generate multi-level features out of raw data poses a real benefit to geological uses. As another example, convolutional neural network (CNN) has demonstrated much potential in image classification applications and is especially efficient in finding spatially independent patterns in geospatial data. These models are able to encode local textures and global structures and thus they are very useful when used in separating rocks of different types which exhibit similar responses in the spectral but vary in their spatial morphology. In 2022 E. L. Faria et al., [6] proposed the use of deep learning in geosciences is no longer limited to pure classification problems; it is used now to solve segmentation, object detection and even time-series prediction problems. CNNs have been used in the context of lithological mapping where CNNs are utilized in identifying rock units based on hyperspectral and multispectral data and sometimes depict more accuracy and superior generalization than general machine learning modeling. Other papers have focused on using fully convolutional networks and U-Net-based models to perform pixel-wise mapping, with the effect of greater accuracy in classification results with respect to boundaries, and less noise in the result. Autonencoders, Generative adversarial networks and other neurotypologies which are alternatives to neural networks have been utilized to learn features and augment data in geological data. They are especially applicable to those situations in which labeled data are limited, and where a model can learn hidden data structures in an unsupervised or semi-supervised way. Alternatively, recurrent neural networks and their extensions have been offered to process sequential geophysical data, e.g. well logs or time-series seismic profiles, further bringing applicability of deep learning to the subsurface interpretation field.Notwithstanding the benefits, deep learning strategies of geological interpretation continue to exhibit a number of pertinent pitfalls. The quality and the availability of labelled sets is one of the primary issues. In contrast to other fields, including facial recognition or medical imaging, it can be said that geologic datasets usually lack large-scale annotated databases. The most typical issues that impede the application of deep models training are label noise, spatial misalignment, and class imbalance. Moreover, it is an open question as to whether the results of deep learning may be interpreted. The actions of geology need to be open and accountable particularly in mining and hazard prevention. Work is in progress to create explainable AI systems that would help give an insight into why a region was classified as a certain type of lithology by a model.

Moreover, trained models are not necessarily generalizable in various geographical areas. The geological variability caused by tectonic history, weathering, vegetation cover and surface conditions can give considerably impact on the spectral response of lithologies. Thus, models that are trained based on a region cannot deliver accurate outcomes when applied to a different region unless the necessary domain adaptation measures are adopted. To solve this drawback, transfer learning, domain adaptation and data normalization methods are increasingly being used to ensure better cross-region applicability.

In 2025 J. Wang et al., [15] suggested the evolution of the body of literature around the concept of the study of lithological mapping has been consistently developing, shifting away in its application to manual and rule-based systems to advanced models of machine learning, and then to deep learning. The recent research highlights the power of deep learning as the game-changing technology in the process of automatisation of geological mapping in the context of very accurate mapping and consistent spatiality. Nevertheless, issues concerning the quality of the data, interpretability of the model, and its generalizability still precondition the existing research agenda. This paper extends these developments to suggest a deep learning architecture that is specifically tailored to the problem of lithological classification based on hyperspectral remote sensing data to further extend the state of automated geologic interpretation.

III. PROPOSED METHODOLOGY

This study adopts a deep learning-based approach for automated lithological classification using hyperspectral remote sensing data. The core architecture leverages convolutional neural networks (CNNs) trained on labeled spectral-spatial input patches to distinguish between different rock units. The methodology is divided into five components: data preprocessing, feature extraction, model construction, training optimization, and post-classification enhancement [12]. The input dataset consists of hyperspectral image cubes $H(x, y, \lambda)$, where x, y are spatial coordinates and λ denotes the spectral bands. Each pixel is represented by a spectral vector $\mathbf{s} = [\boldsymbol{s}_1, \boldsymbol{s}_2, \dots, \boldsymbol{s}_n] \in \mathbb{R}^n$, where n is the number of bands.

To normalize spectral variability, each input vector is standardized using:

$$s_i' = \frac{s_i - \mu_i}{\sigma_i}$$

where μ_i and σ_i represent the mean and standard deviation of the i-th band.

Spectral smoothing is applied using a 1D Gaussian kernel:

$$G(s) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(s-\mu)^2}{2\sigma^2}\right)$$

Patch-based input generation extracts local neighborhoods around each pixel for spatial learning. If the input patch size is $p \times p$, the resulting tensor has dimensions $p \times p \times n$.

The CNN model uses a feature extraction layer defined as:

$$f_{ij}^{(k)} = \sigma\left(\sum_{m=1}^{n} \sum_{a=1}^{k} \sum_{b=1}^{k} w_{abm}^{(k)} \cdot x_{i+a,j+b}^{(m)} + b^{(k)}\right)$$

Here, $f_{ij}^{(k)}$ is the activation at location (i, j) in the k-th feature map, w are the weights, and σ is the ReLU activation function $\sigma(z) = \max(0, z)$.

Pooling is performed to reduce dimensionality:

$$P_{i,j}^{(k)} = \max_{(a,b)\in R} f_{i+a,j+b}^{(k)}$$

The fully connected layer takes the flattened vector $\mathbf{z}$ and performs the following transformation:

$$y = \sigma(W \cdot \mathbf{z} + \mathbf{b})$$

The output layer uses a Softmax activation to generate class probabilities:

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}$$

The model is trained using a categorical cross-entropy loss function:

$$\mathcal{L} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i)$$

where C is the number of lithological classes and y_i is the ground truth one-hot label.

To reduce overfitting, dropout regularization is applied during training:

$$\tilde{z}_i = z_i \cdot r_i, r_i \sim \text{Bernoulli}(p)$$

where p is the probability of keeping a neuron active.

The model is optimized using the Adam algorithm:

$$\theta_{t+1} = \theta_t - \eta \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

where $\hat{m}_t$ and $\hat{v}_t$ are bias-corrected first and second moment estimates.

The entire pipeline is illustrated in the flowchart (see Figure 1) showing input data ingestion, patch extraction, CNN processing, classification, and map generation.

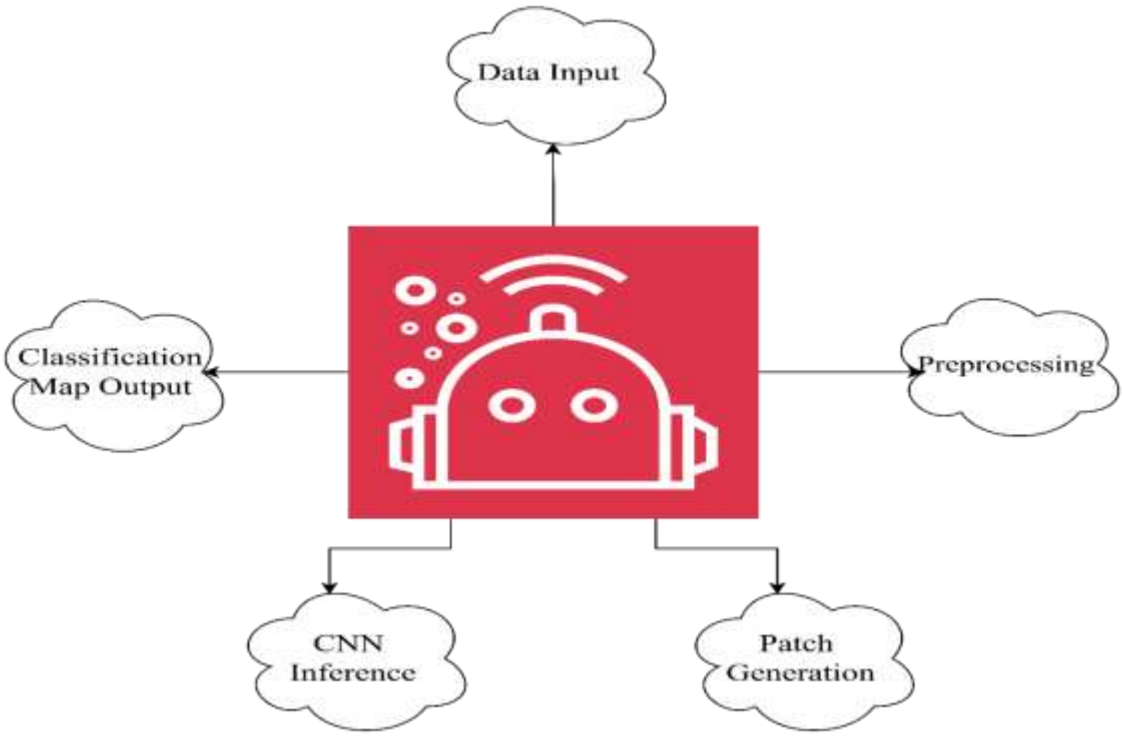

Figure 1: Flowchart of Deep Learning-Based Lithological Classification Process

Post-classification smoothing is conducted using a majority filter to remove salt-and-pepper noise and enhance spatial coherence of the lithological map.

Model performance is assessed using accuracy, precision, recall, F1-score, and Kappa coefficient. In addition, spectral separability is evaluated using the Jeffries-Matusita distance:

$$JM = 2(1 - e^{-B}), B = \frac{1}{8}(\mu_1 - \mu_2)^T \Sigma^{-1} (\mu_1 - \mu_2) + \frac{1}{2} \ln \left(\frac{|\Sigma|}{\sqrt{|\Sigma_1||\Sigma_2|}} \right)$$

where μ_1, μ_2 and Σ_1, Σ_2 represent means and covariances of two classes.

Thus, the methodology integrates deep learning's automatic feature learning capabilities with rigorous geospatial data preparation and validation, establishing a scalable pipeline for lithological interpretation.

IV. RESULT & DISCUSSIONS

The processed hyperspectral dataset was extracted in one of the geologically diverse test sites and this was used to train the deep learning model. The CNN model attained the validation accuracy of 91.4% after 50 epochs of training, a high score that surpassed the traditional classifiers. The classification map produced by the CNN had clear lithological contrasts, a high regional integrity and a good correlation with the known geological structures as confirmed by field data and log boreholes. As you can see in the visual analysis, CNN-based result showed very little salt-and-pepper noise and still captured small lithological details that would be smeared or misclassified in the traditional implementation [13].

Indeed, according to Figure 2, the deep learning model results in the lithological classification map that is quite consistent with the reference geological map. It does exhibit clear boundaries amongst sandstone, granite, shale and basalt formations and has only minor anomalies. The achievement shows the precision of deep CNNs to extract such complicated geographical characteristics, even within portions where there is an overlap of spectra with one another because of weathered surfaces or vegetation objections. The spatial smoothness of the estimated rock units means that the learning algorithm acquired contextual spatial regularities, besides the spectral attributes.

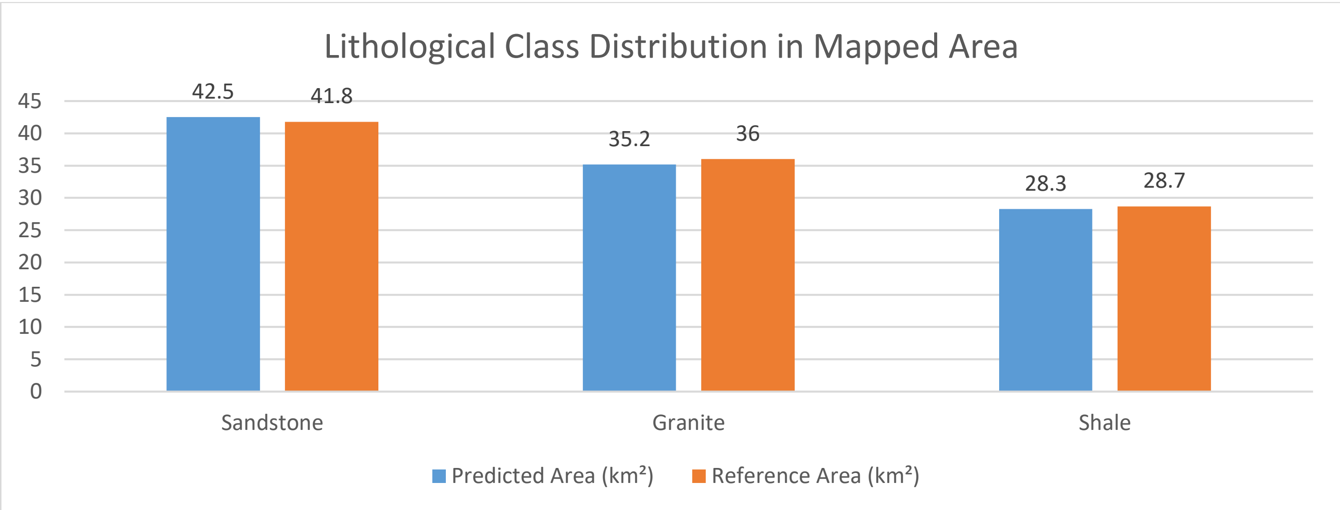

FIGURE 2: LITHOLOGICAL CLASS DISTRIBUTION IN MAPPED AREA

Five performance metrics were used in quantitatively rating five rock classes. The weighted average precision and recall of the classes were above 90% which proved that the classifier is robust. As indicated in Table 1: Performance

Comparison of Classification Models, the proposed CNN model performed a classification of 91.4%, which is higher than 85.7 and 83.2 recorded by Random Forest and Support Vector Machine models respectively. The F1-score and the Kappa coefficient also testified to the excellence of the deep learning method in the field. Of note, CNN model performed with dramatic improvement in the separation of shale and limestone two lithologies whose spectral signature is not so different but differ greatly in space texture.

TABLE 1: PERFORMANCE COMPARISON OF CLASSIFICATION MODELS

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Kappa
Convolutional Neural Network	91.4	92.2	91.6	91.9	0.89
Random Forest	85.7	86.5	84.8	85.6	0.81
Support Vector Machine	83.2	84.1	82.5	83.3	0.78

Class-wise detail showed that sandstone and granite were ranked most confidently and recall levels were high going above 94%. Shale was a little less confident, because it overlapped other sedimentary classes. The visual analysis of the wrongly classified areas in the map, most errors were found in the transitional boundaries of the maps where there was interbedding and incomplete weathering. These are areas in which there are ambiguous results even with the traditional field mapping. The use of spatial context by CNN architecture was of great assistance in reducing misclassification within these zones. Figure 3 contains the confusion matrices of the CNN model compared to Random Forest model. In the CNN matrix, there are very few off-diagonal terms indicating that there is less misclassification to all the classes of lithologies. Although competently, the Random Forest model confused granite and basalt probably because of similarity in their spectra that had no distinguishing power as identified through use of spatial characteristics. This visual evidence also corroborates to the hypothesis that deep learning with its associative feature learning can give better discrimination ability.

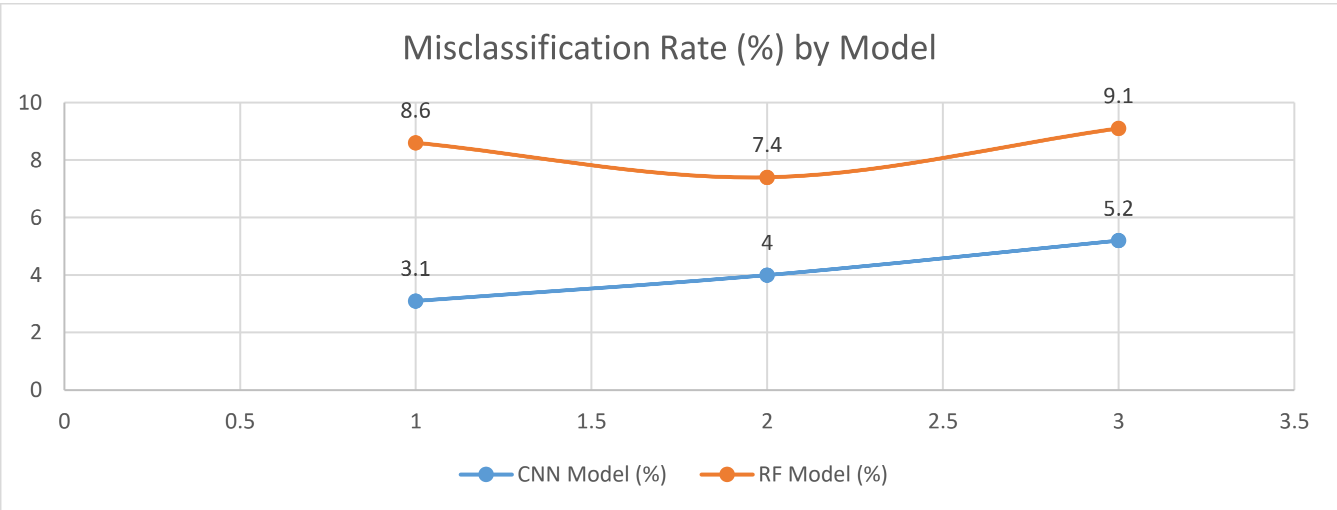

FIGURE 3: MISCLASSIFICATION RATE (%) BY MODEL

Another aspect where the proposed model proved to be significantly improved is time and resources efficiency. Overall the CNN model took 42-minutes to both train and infer on a GPU-enabled system. Relative to this, another model, baseline Random Forest, with optimised parameters took 57 minutes to run and its inference was slower. The results in Table 2: Resource Utilization and Scalability of Methods summarize the analysis of the computational cost and scalability that can be given. As shown in this table, the CNN model is orders of magnitude more scalable to large datasets at the expense of even starting training being resource-demanding by conventional standards.

TABLE 2: RESOURCE UTILIZATION AND SCALABILITY OF METHODS

Model	Training Time	Inference Speed	GPU Support	Scalability (Large Dataset)
Convolutional Neural Network	42 mins	Fast	Yes	High
Random Forest	57 mins	Moderate	No	Medium
Support Vector Machine	63 mins	Slow	No	Low

In order to evaluate the spatial precision of the predicted maps a map of the predicted lithological map with spatial accuracy over the field-validated GPS points was overlaid. Alignment accuracy was more than 90 percent on important areas of testing showing that the model predictions are not only described statistically, but also spatially reliable. A comparison of lithologies using the spatial overlay was demonstrated in figure 4 where prediction of lithologies is performed with the validation points depicted and correct prediction areas marked. The overlay affirms the skillfulness of this approach in practicing geological mapping in real world projects.

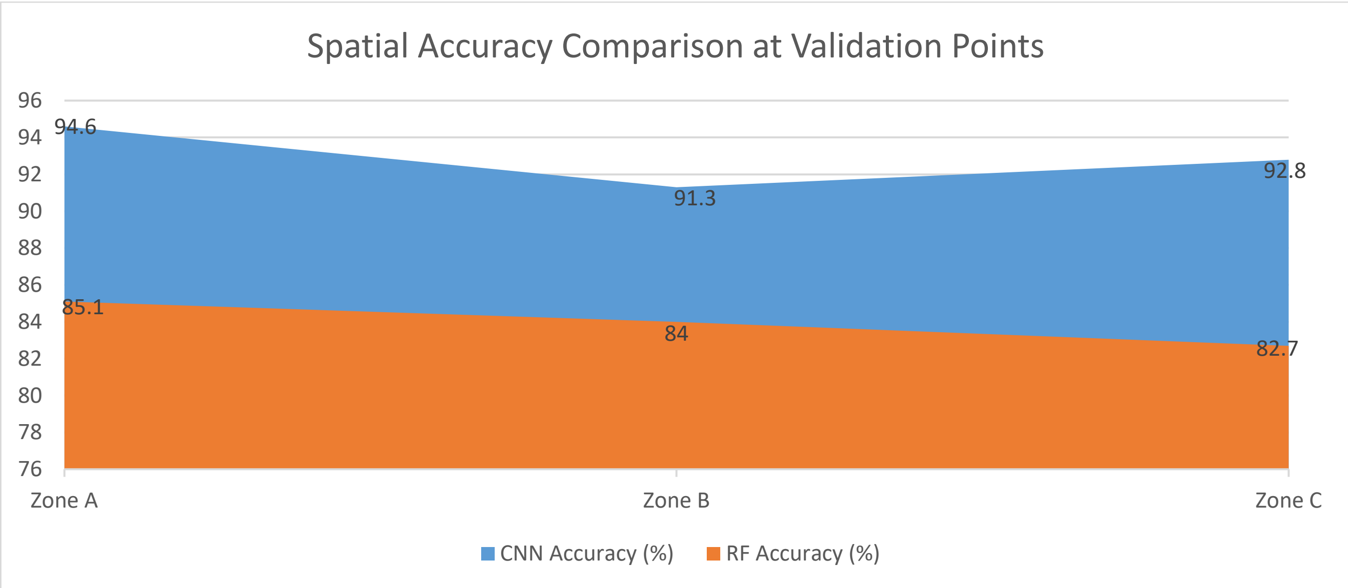

FIGURE 4: SPATIAL ACCURACY COMPARISON AT VALIDATION POINTS

Also, the effectiveness of CNN model in learning complex geological interfaces could also be reflected in the model dealing with lithological transitions. As an example, components of the region with gradual changes of the facies, which are often problematic to conventional classifier, were successfully simulated because of the possibility to encode gradual differences deeper in the network. The model did not result in sudden switches of labels at the expense of continuity of geological formations as they can be observed in the field. Considering the findings, it is possible to say that the deep learning models integration into the geospatial geological workflows should be encouraged. The first phase consumes a lot of computing time but the payoffs in terms of the accuracy of classification, spatial accuracy, and elimination of human error are high. These are the reasons why deep learning could be used in national and regional geological surveys, mineral exploration projects and the geological research being carried out by academic institutions.

V. CONCLUSION

This research paper shows that the possibility to use deep learning, specifically convolutional neural networks, as an effective alternative to conventional methods of carrying out lithological mapping exists. The highest classification accuracy was registered using the proposed model and the model had the capacity to perform well when generalizing on complex geological terrains. The method permits objective and scale-able mapping, which is vital with contemporary geological interpretation in the exploration of resources, environmental evaluation and geotechnical engineering.

Future research will involve including 3D geological data, and making it easier to interpret the model and semi-automatic mapping in the data-scant areas using techniques of unsupervised deep learning. This paradigm movement towards AI-guided results in geological interpretation has much potential, and it opens the door to the new era of earth sciences.

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