# Lithology and fluid prediction using AI algorithms around the Shrek area in the Norwegian Sea

## Introduction

In this work, we show the result of applying Rune Inversion and Machine Learning (ML) algorithms for lithology and hydrocarbon prediction to the seismic and well data in the Norwegian Sea in 2021. We are dealing with post-seismic data and considering the proposed techniques as an alternative and additional scanning tool to derisk the prospects. We study the area around Shrek and along Skarv discovery at Fangst Group formations, which often have hydrocarbon-bearing sandstones. Several wells penetrated reservoirs with success. A dry hole was one of the latest announced results of drilling in the studied area in 2024.

The possibility of using ML methods was considered by many authors, mainly to find similarities among attributes to delineate geological bodies. Some software proposed identifying rock physic parameters using wells and seismic attributes of the offset seismic data (e.g., software like Emerge (Hampson-Russell) since 2006, Paradise since 2008, Paradigm, SeisFacies module, 2018).

We investigated the possibility of direct fluid prediction using machine-learning methods with no shear-wave-related information available in our early work. We showed that it is possible to predict fluid when only seismic data is available and when we also have inverted volumes. (Karaseva & Kalashnikova 2021). We use Rune Inversion as a post-stack inversion algorithm to produce non-linked Vp and density, and then we compute derivatives like volume of clay and porosity (Øverås & Kalashnikova V, 2021; Gyllenhammar, 2020). Learning from the well-logs data and recognising target parameters from the inverted seismic data and their derivatives gives a good scanning tool for the target parameter, resulting in fluid-type prediction.

## Data and Method

The study area is in the Haltenbanken of the Norwegian Sea shelf, Fangst Group, Figure 1.

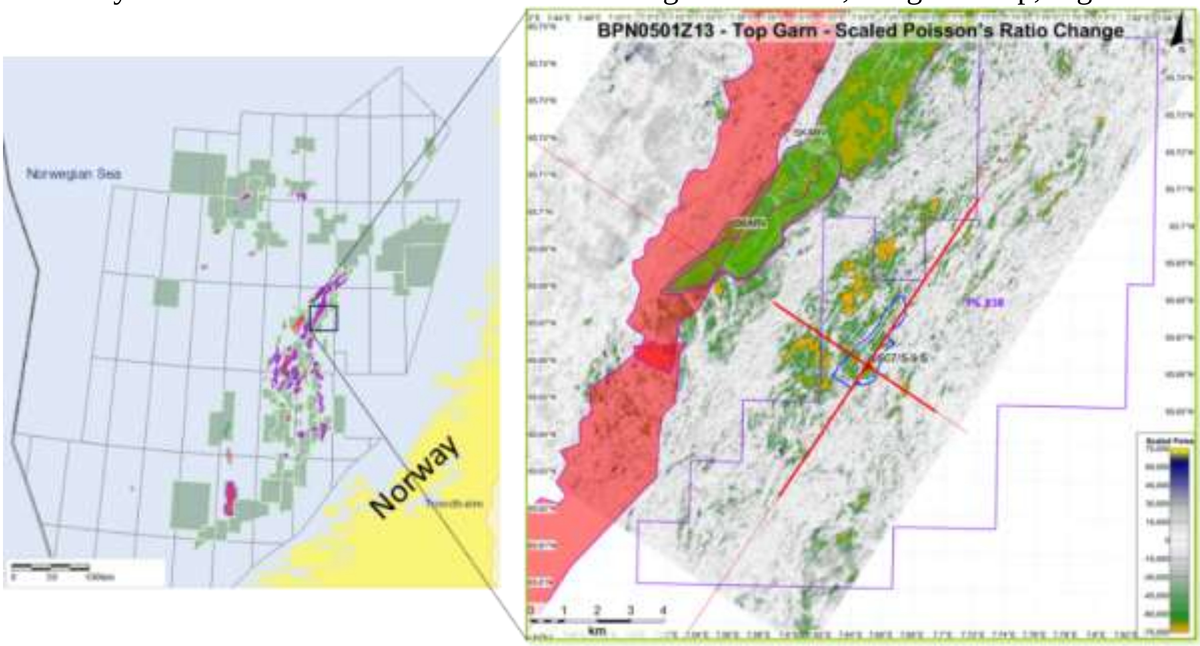


**Figure 1.** Map with study area location (www.npd.no) and the scaled Poisson Ratio attribute of PGS BPN0501Z13 data through the prospect in one Fangst formation and with outlined discoveries in red and green of all formations.

The PGS BPN0501Z13 post-stack seismic data were used to compute inverted volumes of Vp and density using the Rune Inversion algorithm. Then, we used the Gyllenhammar formula to compute the volume of clay (Gyllenhammar, 2020), and we used the conventional approach to compute porosity when knowing the density and volume of clay. The initial model for inversion were build using 6507/3-6, 6507/5-1, 6507/5-5, 6507/5-9A, 6507/5-9S, 6507/6-1, 6507/6-2 wells' logs data. There were no quality density logs available for the study. Also, only a Neutron porosity log was available to study with higher-than-expected parameters and no possibility for calibration. It must be considered when analysing the result.

In constructing predictive models for hydrocarbon accumulation, we utilised the 151 wells from the Norwegian Sea. To "learn", we used well logs of p-wave velocity (from a sonic log), density, p-impedance, clay volume, total porosity, and water saturation, which served as the target parameter. We use the inverted volumes of the same parameters to recognise or predict target parameters. A value of 1 was assigned to water saturation when pores were filled 60% with hydrocarbons, and 0 - for the brine case, Figure 2. We did this in a similar way to the already published work (Karaseva & Kalashnikova, 2021)

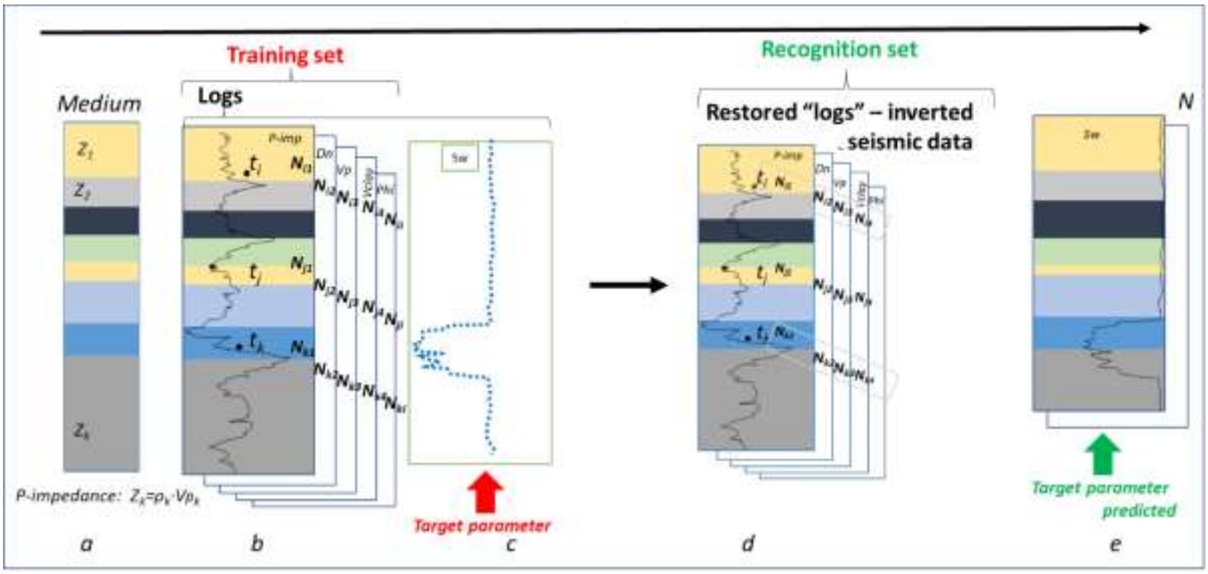


**Figure 2.** Schematic illustration of the training and recognition data extraction. *a* and *b* – medium and recorded though it logs data, *c* – target parameter to be predicted, *d* – recognition set (rock properties restored using inversion processes) to predict the target parameter *(e)*.

The available data underwent minimal preprocessing and was divided into train, validation, and test sets (Burkov A., 2019). One well with HC presence (well 6507/7-1) served as the test set, while data from the remaining 150 wells were randomly divided into train and validation sets (70%/30%). Subsequently, models were constructed using the train set and evaluated on the validation set. The test dataset was kept separate and used to assess the models' performance.

We used the Grid Search optimisation algorithm to find an optimal set of hyperparameters on which classification performs the best and tune them. Secondly, we performed cross-validation to evaluate our machine learning models on 150 wells data. We used K-Fold cross-validation with k= 5 (4/5=120 wells - train, 1/5=30 wells – validate). Cross-validation was performed to evaluate machine learning models on 150 wells.

We used the following machine learning classification algorithms to build predictive models: Logistic regression (LogReg), Gaussian Naïve Bayes classifier (GNB), Support Vector Machine (SVM) classifier, Gradient Boosting classifier (GBC), Multi-layer Perception classifier (MPLC). We employed precision, recall, and F1 score metrics to assess the effectiveness of classification models. Two algorithms of LogReg and GNB did not show prediction at all, and we can observe data over fill or have very little spread on the result maps (Figure 3). This abstract demonstrates all algorithms for analysis.

**Result**

Figure 3 shows the result of predicting HC by five machine learning algorithms at Fangst Group.

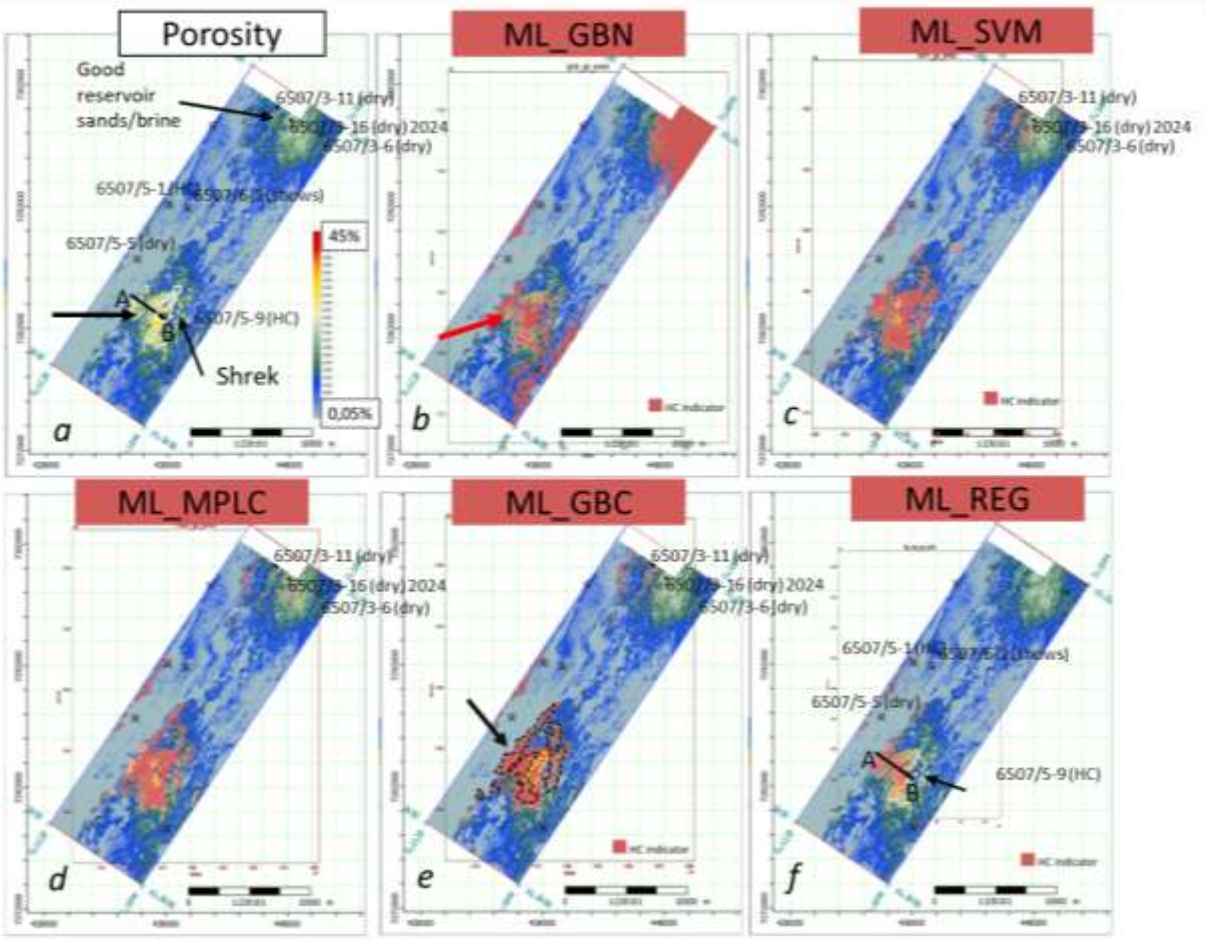


**Figure 3.** Maps at the top Fangst GR reservoir sand of 50 ms average values of porosity (*a*) with overlayed HC prediction (red dots) by different machine learning methods: *b* – Gradient Boosting classifier, *c* - Support Vector Machine (SVM) classifier, *d* - Multi-layer Perception classifier, *e* - Gaussian Naïve Bayes classifier, *f* - Logistic regression.

The first map displays the porosity of the reservoir layer (Fangst Group), while the remaining maps have porosity with overlaid red dots indicating hydrocarbons (1 (red) - HC, 0 - brine). We can observe good porosity over the Shrek area (estimated by Rune Inversion algorithm) with HC indicator of different spread on all ML maps. The northern part of the porosity map, well 6507/3-2, also indicates good sands and high porosity that matches the NPD description of the good brine reservoir. However, the ML GNB algorithm incorrectly indicates HC all over the structure. The other four algorithms show the correct brine indicator over the northern structures. LogReg shows minimum indicator (as per test); thus, ML SVM, ML_MPLC, and ML_GBC give similar predictions, increasing trust. The standing out Skarv discovery (by all methods, even though porosity is lower in that part) also adds trust to the prediction result.

The Shrek area must be analysed in comparing the ML results. The possible outlines that can be added to the Shrek discovery to analysis are shown on the first Figure 3 *e*. The most interesting part is that the west deeper area confidently stands on all methods as HC-containing. Another interesting result is that the well 6507/3-16 were announced dry recently, in 2024. It is placed in good porosity sandstone; however, ML techniques do not confirm hydrocarbon. In addition, 6507/3-11 possibly missed a structure with good sandstone, where hydrocarbons are possible or, at least, shows are likely.

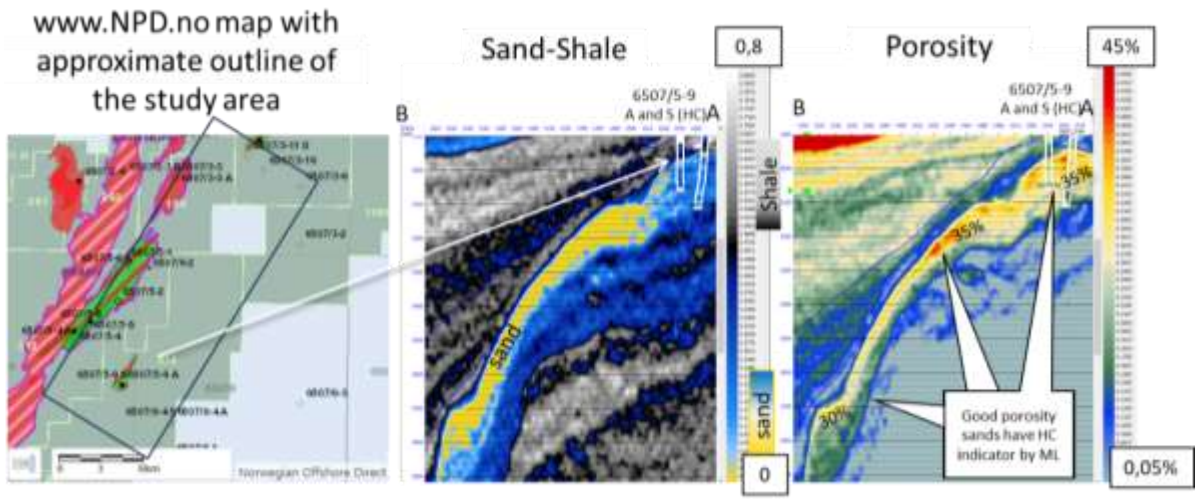


**Figure 4** Map of data location overview and time section through the wells 6507/5-9 A and S – Shrek reservoir (Norwegian Sea), corresponds to the line BA on Figure 3. **Due to the absence of quality porosity logs, data must be analysed relatively, and we should not rely on absolute values.*

## Conclusions

In the investigated region, the application of both Rune Inversion and machine learning (ML) techniques yielded a coherent prediction of hydrocarbon distribution, a conclusion corroborated by recent drilling activities. This finding underscores the alignment between predicted hydrocarbon locations and actual reservoir positions. Predictive accuracy can be enhanced by refining the precision of inversion techniques and the computation of clay and porosity parameters. Integration of precise porosity and density logs data holds promise for such improvements. Furthermore, fine-tuning the ML algorithm has the potential to facilitate a more intricate evaluation, thereby augmenting its utility for nuanced geological analyses.

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