

URTeC: 4265623

Harnessing AI and Computer Vision for Efficient Geothermal Field Exploration and Prospect Evaluation

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Copyright 2025, Unconventional Resources Technology Conference (URTeC) DOI 10.15530/urtec-2025-4265623

This paper was prepared for presentation at the Unconventional Resources Technology Conference held in Houston, Texas, USA, 9-11 June 2025.

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Abstract

The exploration phase of geothermal fields usually includes identifying potential geothermal prospects and drilling exploration wells. Identifying potential prospects is often carried out based on experts' knowledge of the area of interest, surface manifestations, analog fields and/or historical activities in the region. However, in green, new potential fields with no surface manifestation (blind fields) is more challenging to secure such information and hard to identify potential prospects for further investigation. In this study we provide and assess an Artificial intelligence (AI) tool that can identify, narrow down and rank the potential geothermal reservoir fields in an area of investigation. This tool significantly reduces the resources allocated for geothermal field exploration.

Conventional and hybrid machine learning (ML) techniques along with computer vision have been used to address our objective. A combination of different machine learning algorithms has been used. The models were trained on approximately 650K data points and tested on a different data set with almost 650K data points then deployed on multiple States in the western US region. High-resolution input images carrying certain surface/subsurface features needed for geothermal exploration were used for training. The input data was preprocessed, filtered and normalized before the training process and then ML models were optimized and tested.

Recall, precision and F-1 score were evaluated for the constructed models. A hybrid approach was adopted with an overall accuracy of more than 90%. The outcome of the models was cross-checked among all models, known geothermal fields, and experts' recommendations on areas of investigation. The results were used to produce probabilistic ranking (P25, P50 and P75) for the top prospects in the region and generate a heatmap with a probability contour plot for the area of investigation. The model showed a great alliance with the experts' prediction of the geothermal potential presence.

This AI tool is an immensely powerful tool especially for early-stage exploration and remote green locations. This Hybrid-AI can detect the locations of geothermal fields accurately, quickly and it is applicable everywhere, not just around the area of initial investigation. Overall, this AI tool helps reduce uncertainties, cut exploration costs, and fast-track clean energy projects.

Keywords: Geothermal, Machine Learning, Computer Vision, Deep Learning, Western US

Introduction

Geothermal energy is a sustainable, baseload power source, yet the discovery of new resources especially blind geothermal systems that lack surface expressions remains a significant challenge (Richards and Blackwell, 2002). Geothermal exploration traditionally relies on geological, geochemical, and geophysical surveys to find evidence of subsurface heat, fluids, and permeability. However, many geothermal systems are "blind," meaning they lack surface manifestations, making discovery challenging (AlGaier et al., 2024). These concealed systems, often found in tectonically active regions like the Basin and Range, are thought to represent the majority of untapped U.S. geothermal potential (Williams et al., 2009). blind systems require advanced subsurface interpretation and integration of indirect data types, making their exploration risk-prone and resource-intensive (Coolbaugh et al., 2007).

To reduce exploration uncertainty, play fairway analysis (PFA) has emerged as a framework to integrate diverse datasets; geological, geochemical, and geophysical into a probabilistic geothermal favorability map (Faulds et al., 2017). However, traditional PFA methods rely on subjective weightings or basic statistical models. In recent years, ML techniques have been applied to geothermal exploration to augment expert driven analysis. ML can integrate diverse datasets, detect subtle patterns, and handle large data volumes more efficiently than manual methods (Faulds et al., 2020). In this section, a brief background on previous work that has been done to utilize ML in geothermal exploration, the algorithms used, data and methodology.

A variety of ML algorithms have been explored for geothermal resource prediction. These range from traditional shallow learners to advanced deep learning models, each with strengths and limitations in the geothermal context. Tree-based ensemble methods such as random forest (RF) and gradient-boosted (GB) trees (e.g., extreme gradient boost (EGB), LightGBM) are widely used in geothermal exploration. They effectively model non-linear relationships and can handle mixed data types (Shahdinet et al., 2021). Supervised ML models such as RF, support vector machines (SVM), and multilayer artificial neural network (ANN) have been used to predict geothermal potential based on labeled datasets of known systems (Smith et al., 2023). For instance, Smith and colleagues applied a Bayesian neural network on the Nevada play fairway dataset, generating probabilistic favorability maps that improved predictive performance and interpretability. Their hybrid model, which combined supervised and unsupervised approaches (e.g., PCA + clustering), revealed subtle spatial relationships between structural and geochemical indicators that were previously overlooked.

Other studies have focused on remote sensing and computer vision. Moraga et al. (2022) used thermal infrared, spectral, and topographic satellite data, processed via convolutional neural networks (CNNs), to detect geothermal surface expressions. Remarkably, their model, trained on Brady Hot Springs, accurately predicted the Desert Peak system which is an archetypal blind field, achieving 92% intra field and 75% cross field accuracy. These results validate the use of AI in identifying geothermal anomalies even in the absence of surface clues. In greenfield areas with limited prior exploration, unsupervised ML also plays a role. Mudunuru et al. (2023) applied clustering and dimensionality reduction methods to group geothermal features in the Tularosa Basin. The approach identified new targets consistent with expert assessments, showcasing ML's utility in early-stage screening. Despite these advances, challenges persist. Geothermal datasets are often sparse, noisy, and heterogeneous. Many ML models suffer from overfitting due to small training sets, or from poor transferability across geologically distinct regions (Faulds et al., 2020; Goodfellow et al., 2016). Model interpretability and expert integration also remain essential to avoid spurious predictions and ensure geological credibility.

Based on the abovementioned analysis, the development of a global tool that can utilize existing data to identify potential resources is much needed. Such a model can survey vast and remote areas in a timely efficient manner. Combining ML, computer vision and domain knowledge in geothermal exploration is a significant step in order to precisely and efficiently identify more resources. In this article, an AI tool is created to give a probabilistic prediction of geothermal resources presence. Conventional and hybrid ML techniques along with computer vision have been utilized to build multiple confident layers that can predict the presence of geothermal resources. The models were trained on approximately 650K data points in an explicitly identified region and tested on a separate 650K data set, then deployed on multiple states in the

western US region. A combination of different ML algorithms has been used; Logistic regression classifier (LGC), k-nearest neighbor (KNN), gaussian naive bayes (GNB), linear support vector machine (LSVM), radial basis function support vector machine (RBF), adaboost (ADB), RF, GB, EGB, and ANN to build upon previous efforts by developing a scalable hybrid AI workflow to detect and rank geothermal prospects. This framework aims to reduce uncertainty in early-stage geothermal exploration and support cost-effective clean energy development.

Theory and/or Methods

Data was collected in the form of high-resolution images. High resolution images are captured, filtered and fed to the models. Each image contains a certain feature that is crucial to the geothermal exploration process as shown in Figure 1. The images carried tectonics, advection, heat source proximity and heat flow information. A total of 15 input RGB heatmaps with information regarding proximity to faults, volcanic activity and well springs, and igneous facies outcrops as well as Moho depth, crustal thickness, temperature gradients, and topography were used in models construction. The target is a satellite image with known geothermal locations. The data used in building these models is available to for the entire U.S. and expanding to cover the rest of the world which supports the scalability and deployment of this work.

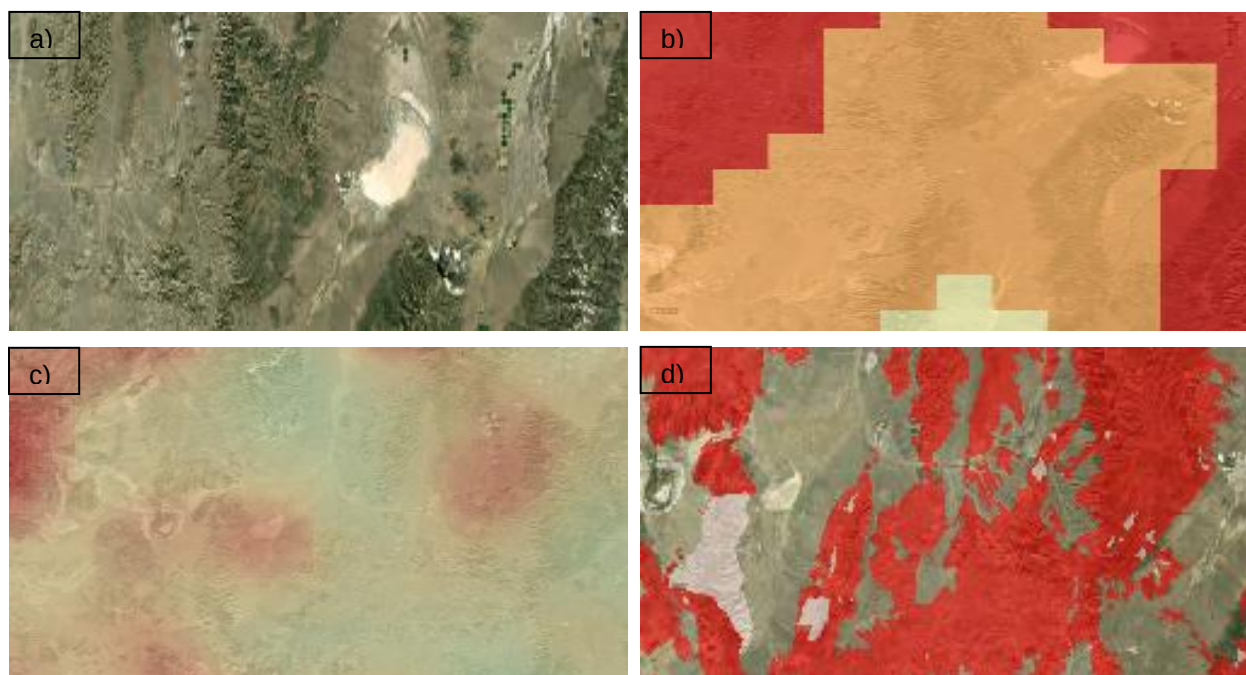


Figure 1. Shows a sample of the input images captured from Project InnerSpace. a) satellite image, b) heat flow, c) geothermal gradient, d) Igneous facies.

Since some models tend to be overly optimistic and others tend to be more pessimistic, a hybrid approach was adopted to utilize the strengths and avoid the drawbacks for each algorithm individually. 10 algorithms were trained, fine-tuned, and optimized on 650K training pixels in an explicitly defined region. Then, the algorithms were tested by applying the models on a new region and evaluating their performance. F-1 score, recall and precision were evaluated, and models were filtered based on their performance. The decisions of the successful models were stacked to produce a single output on the presence of geothermal resource in the form of a heatmap. The degree of confidence in the output can be adjusted by modifying the stacking technique which allows the user to run different scenarios. The outcome of the models can be exported in a GeoTiff format to be used in GIS software and coupled with other essential criteria for site selection. Figure 2 illustrates the detailed methodology followed in this paper.

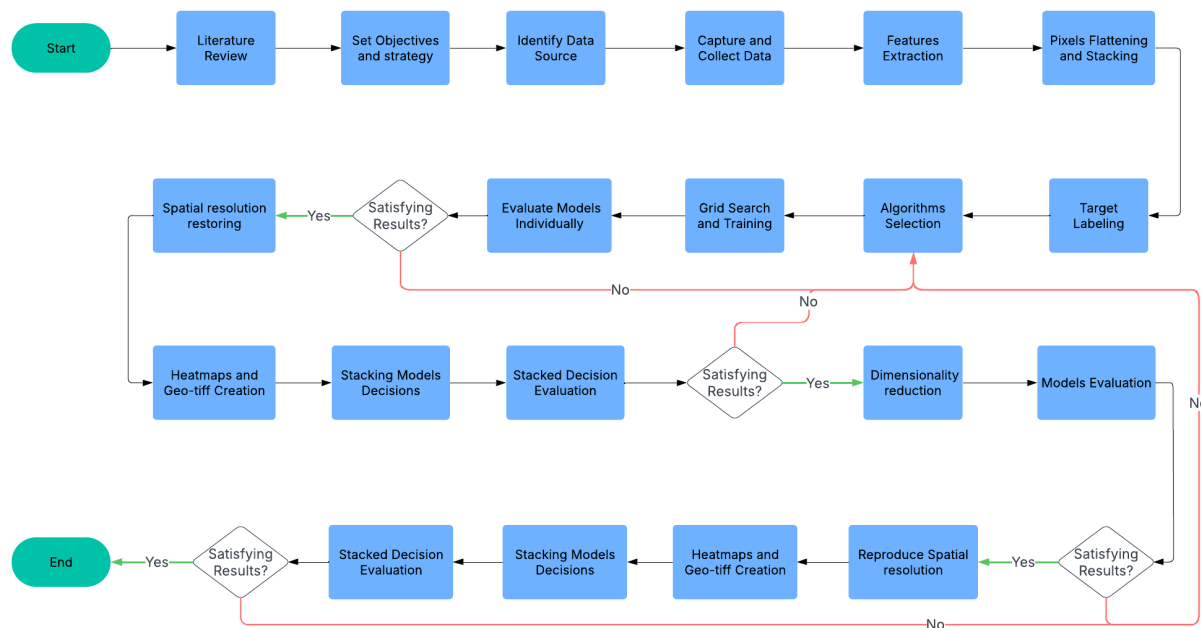


Figure 2. The process flowchart followed in this paper.

Data Preprocessing and Model Building

High-resolution images and datasets utilized in this study were sourced from GeoMap™, an open-access geothermal mapping platform developed and hosted by Project InnerSpace. GeoMap™ integrates over 400 distinct data layers, encompassing harmonized geological, geophysical, infrastructural, environmental, and socioeconomic information relevant to geothermal exploration. The platform synthesizes diverse global data sources into a comprehensive and regularly updated spatial database, enabling advanced analytics, comparative assessments, and screening for geothermal resource potential at both regional and global scales. GeoMap™ can be found at 'geomap.projectinnerspace.org'. The captured High-resolution images were preprocessed before being fed to the models. Both satellite images and heatmaps have dimensions of around 150 Km length by 90 Km width. The resolution of the images is 5980X3620 pixels with 3 channels RGB, which translates to around 25m/pixel. The resolution of the images was then reduced to one tenth of their value to produce images with resolution of 598X362 and 0.25Km/pixel. This resolution still maintains high resolution while significantly reducing the computational needs for data handling and training. In addition, this resolution keeps the balance between creating a regional tool while having the capability of identifying promising local fields.

The data was then normalized, and multiple-feature extraction filters were applied. Gaussian filters are used in image processing primarily for noise reduction and smoothing, while also preserving image edges and features due to their unique properties derived from the Gaussian distribution (Eswar, 2015). Difference of Gaussian (DoG) that act as a region detector was applied to create features with enhanced edges and smaller details by subtracting a blurred image (high standard deviation Gaussian) from a less blurred image (low standard deviation Gaussian) (Gonzalez and Woods, 2018). Also, Sobel filter was used to perform a 2-D spatial gradient operation on the input images to enhance the edges, a process that identifies boundaries between regions of different intensities or colors in an image by calculating the gradient magnitude and direction (Woods, 2006). In addition, Hessian filters were applied to detect and enhance structures like edges, vessels, and blobs by analyzing the second-order derivatives of pixel intensities, capturing curvature and rate of change of the gradient (Longo et al., 2020). Lastly, Local statistical filters were used to enhance images by analyzing and modifying pixel values based on their local neighborhood, effectively reducing noise, smoothing edges, and improving overall image quality (Lee, 1981).

Each filter created an enhanced image for all 15 input images with the same resolution. The created feature images were then stacked and flattened to create 649,428 pixel points with 210 corresponding features. Figure 3 shows a visual illustration for building features for each pixel. The target is also a hiRgh-resolution image satellite with locations of know geothermal locations highlighted as green dots on the image. Since DoG acts as a region detector, it was able to detect the regions of known geothermal locations. A mask was then created with geothermal locations as positive and locations with no geothermal locations as negative. This process automatized the labeling of the target images to create training masks. This allowed handling bigger amounts of data in a faster, more standardized and simple way. The created mask was then flattened consistent with the abovementioned flattening process for the input data. This process created a binary domain target value for the 649,428 pixel points.

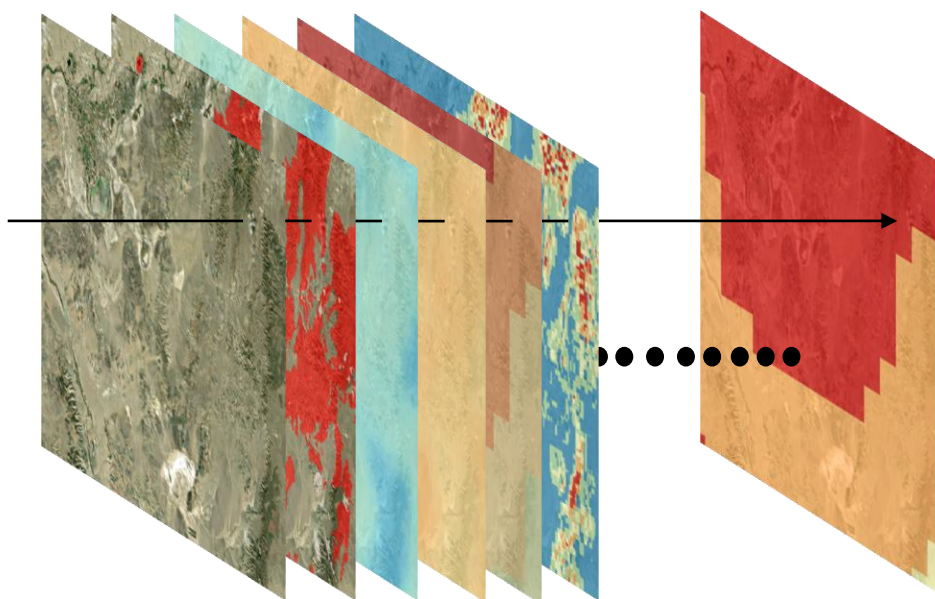


Figure 3. A visual illustration for building and stacking features for each pixel which represents a certain location.

The created dataset was then fed into 10 classifiers with an enormous grid search summarized in Table 1 to optimize the hyperparameters for each model. The best performing hyperparameters/parameters for each model were pickled and saved for further use. The models were evaluated based on F1-Score, recall and precision. The prediction probability of each model was then used to create a heatmap with the probabilistic existence of geothermal resources. The produced outcome has been un-flattened, and it was given back its spatial resolution. A new image was imported with the same resolution for testing. The same aforementioned procedures were followed to create and extract the features and to create the labels. The data was passed through the created models, and a classification report was generated. The decisions of the models were stacked to create a single probabilistic decision on the presence of geothermal fields. The stacking can be adjusted based on the desired level of confidence. Feature importance was evaluated, and a dimensionality reduction was carried out. 140 features were eliminated leaving only 70 features to be used for retraining reduced models. The outcome of these models handled the same way as the original models and reshaped to regain its spatial resolution. Finally, the outcome heatmaps from both reduced and original models were georeferenced to be utilized and integrated in decision-making processes on GIS software.

Results

Different classification algorithms exhibit varying tendencies in their predictions, particularly in binary classification problems where outcomes are either positive (presence of geothermal resources) or negative (absence). Generally, models such as KNNs, ANN, GDB, ADB, and EGB are considered more optimistic, as they often exhibit a higher tendency to predict the positive class (i.e., presence of geothermal resources), especially when the dataset is imbalanced or contains subtle signals (He & Garcia, 2009; Chawla et al.,

2004). This behavior arises from their sensitivity to local patterns (in KNN), their capacity to model complex non-linear relationships (in ANN), and their emphasis on minimizing errors on difficult cases (in boosting algorithms) (Fernández-Delgado et al., 2014; López et al., 2013). Conversely, models like LGC, SVMs, RF, and GNB tend to be more conservative. These models are more likely to favor the majority class (i.e., absence of geothermal resources), especially when there is limited signal strength or when class imbalance is present (Japkowicz & Stephen, 2002; Bishop, 2006). Their conservative nature is attributed to linear assumptions, margin maximization, ensemble averaging, or strong probabilistic priors (Provost & Fawcett, 2001; Bishop, 2006). These tendencies must be accounted for when selecting a model in resource exploration tasks, particularly when false negatives (missing a geothermal prospect) carry higher consequences than false positives. On the other hand, a false positive might lead to an unsuccessful financial decision. However, the scheme in which the ML models are used is to run the positive IDs through an extra screening process in which human screening and other factors can outweigh the influence on the final decision. Figure 4 shows the difference in prediction between each algorithm on the same area of 82 km in length and 50 km in width. Stacking the decision of multiple classifiers eliminates some of the biases created from the design of the algorithms and increases the confidence in the results (He & Garcia, 2009; López et al., 2013).

Table 1. Summarizes the grid search hyperparameters for each model

Hyperparameter	Range	Model
C	[0.001, 0.01, 0.1, 1]	LGC, LSVM
penalty	['l1', 'l2', 'none']	LGC
solver	['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga']	LGC
max_iter	[1000]	LGC
class_weight	['balanced', None]	LGC, LSVM, RF
n_neighbors	[3, 5, 7, 9]	KNN
weights	['uniform', 'distance']	KNN
algorithm	['auto']	KNN
leaf_size	[10]	KNN
—	—	GNB
kernel	['linear'], ['rbf']	LSVM, RBF
degree	[2, 3]	LSVM, RBF
gamma	['scale', 'auto', 0.001, 0.01, 0.1]	LSVM, RBF
coef0	[0.0, 0.1]	LSVM, RBF
n_estimators	[50, 100, 200, 300, 400, 500]	ADB, RF, GB
learning_rate	[0.001, 0.01, 0.1]	ADB, GB
algorithm	['SAMME', 'SAMME.R']	ADB
max_depth	[5, 10, 15, 20] (RF), [3, 5, 7] (GB), [3, 4] (XGB)	RF, GB, EGB
min_samples_split	[2, 5, 10]	RF, GB
min_samples_leaf	[1, 2, 4]	RF, GB
max_features	[5, 10, None]	RF
criterion	['entropy']	RF
bootstrap	[True, False]	RF
oob_score	[True]	RF
subsample	[0.8, 0.9]	EGB
reg_lambda	[0.1, 0.05]	EGB
scale_pos_weight	[1, 10, 25, 50, 75, 100]	EGB
hidden_layer_sizes	[(25,), (50,), (75,), (100,), (25,25), (50,25), (50,50), (10,10,10), (25,25,25), (50,50,50)]	ANN
activation	['logistic', 'tanh', 'relu']	ANN
alpha	[0.00001, 0.0001, 0.001, 0.01, 0.1]	ANN
batch_size	[16, 32, 64, 128]	ANN
learning_rate_init	[0.001, 0.01, 0.1]	ANN

The performance details of each algorithm are shown in Table 2. Since the main target is to predict the presence of geothermal locations which is the minority class, the macro recall and macro F1-score were the main focus in selecting the models to move forward. Varying the threshold in which the algorithm takes the decision of classifying a certain area as a geothermal prospect or not changes the performance of the

models significantly. The threshold of the model prediction was tested and adjusted to get the best performing models. Figure 5 shows the recall vs F1-score for the models with different threshold values. The models selected are the ones that fall in the top right corner in Figure 5 were as they exhibit high recall and high F1-score.

The probabilistic values presented in the heat maps in Figure 4 are normalized and stacked to produce a single outcome heatmaps. The stacked decision heatmaps are shown in Figure 6. The confidence level increases with the increase of the number of models predicting a certain location to be geothermal system. A more conservative approach is also presented by ignoring the highest values produced by x number of models and only using the probability of the presence of geothermal fields from the more pessimistic models. The number of models ignored/used can be determined by the user based on the desired degree of confidence/risk.

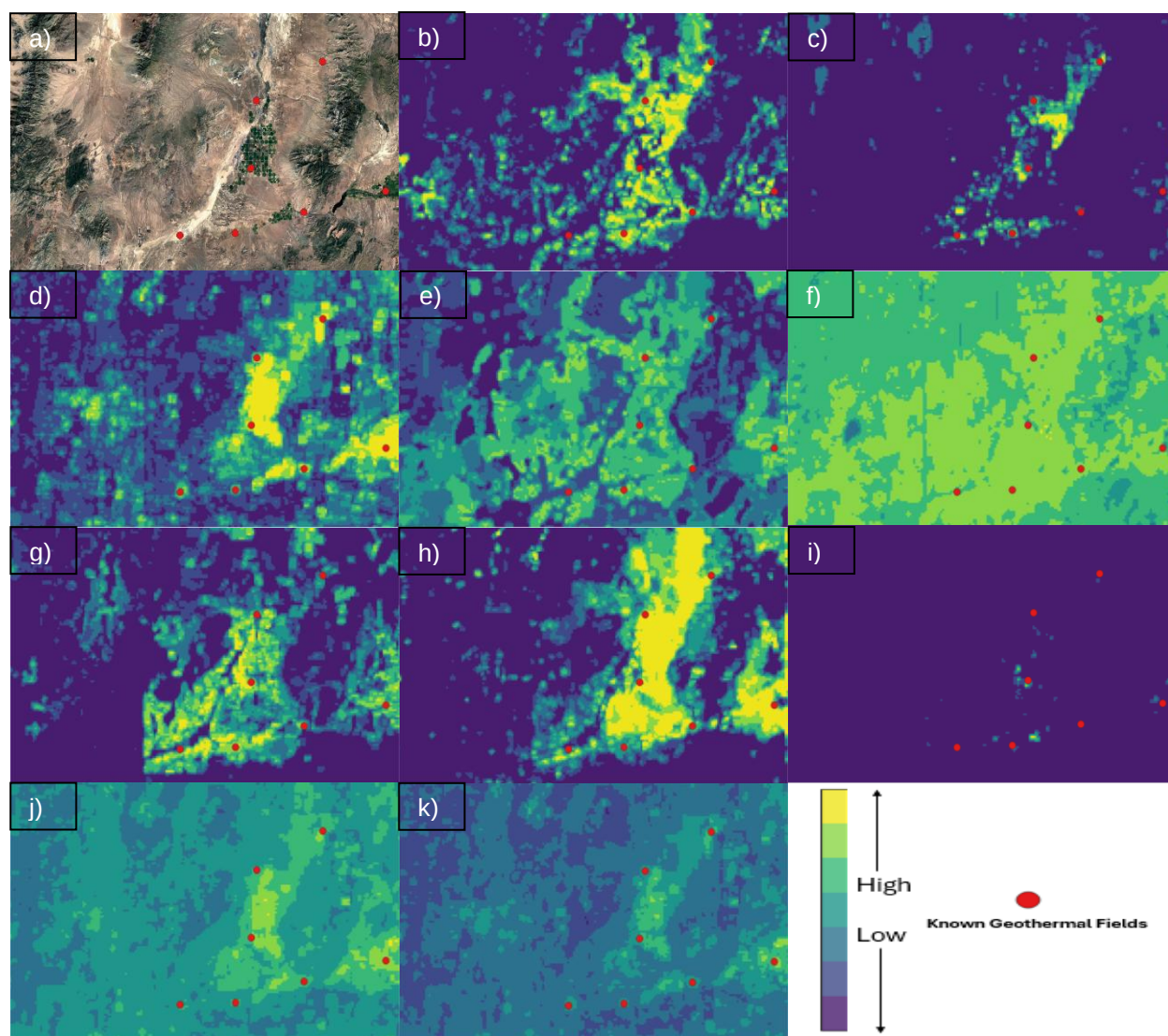


Figure 4. Heatmaps produced for the 82 km length and 50 km width area shown in a) satellite image. b) EGB, c) ANN, d) LGC, e) RF, f) ADB, g) KNN, h) GNB, i) GDB, j) RBF, and k) LSVM probabilistic heatmap predictions. The red dots represent the locations of the known geothermal locations. The hot colors on the heatmap represent high probability of geothermal resources presence. While the cold colors represent low probability of geothermal resources presence.

Moreover, the effect of dimensionality reduction is presented in Figure 7. Initially the models were built by using all 210 features constructed. This increased confusion for the models that can be seen in Figure 7. The unreduced models' predictions tended to show weak to medium hesitant potential signals. Usually,

geothermal systems are formed due to certain natural phenomena that bring heat to the surface. For that reason, it is not common to identify trends in the location of these geothermal systems like following a major fault, subduction zone, etc. In the more confidence layers, the unreduced models were able to assign high potential probability to some of the geothermal locations but failed to identify others with a less clear layout pattern. In some cases, there could be collinearity between input features that can worsen the models' performance. Also, added features can improve targeting over others, in which case removing the less important features can decrease the hesitation in the models. The models' predictions showed higher, more concentrated signals around the locations of geothermal locations after dimensional reduction. On the other hand, the area where there are no known geothermal locations displayed no signal, especially in the high confidence (more conservative) prediction layers. This observation shows less hesitation in the reduced models' predictions since they receive less (could be contradicting) input information. Also, a clearer pattern supported by known geothermal systems locations can be detected in the models' prediction for the potential of presence of geothermal fields.

Table 2. Summary of each algorithms' performance on the testing dataset.

Model	Precision	Recall	F1-Score
LGC	0.86	0.96	0.9
KNN	0.96	0.87	0.9
GB	1	0.97	0.98
ADB	0.54	0.52	0.11
GNB	0.98	0.99	0.99
LSVM	0.95	0.99	0.97
RBF	0.93	0.97	0.94
RF	0.8	0.98	0.86
ANN	0.95	1	0.97
EGB	1	0.89	0.94

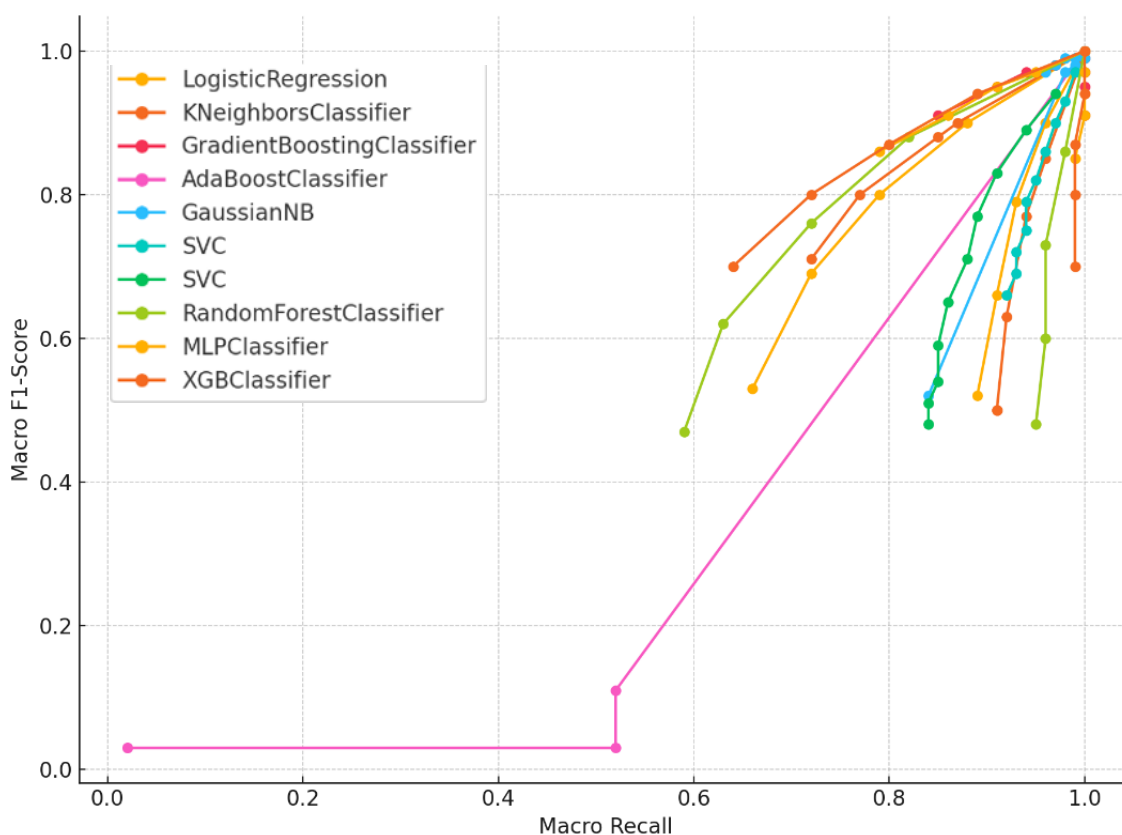


Figure 5. Recall vs F1-score for the models with different threshold values.

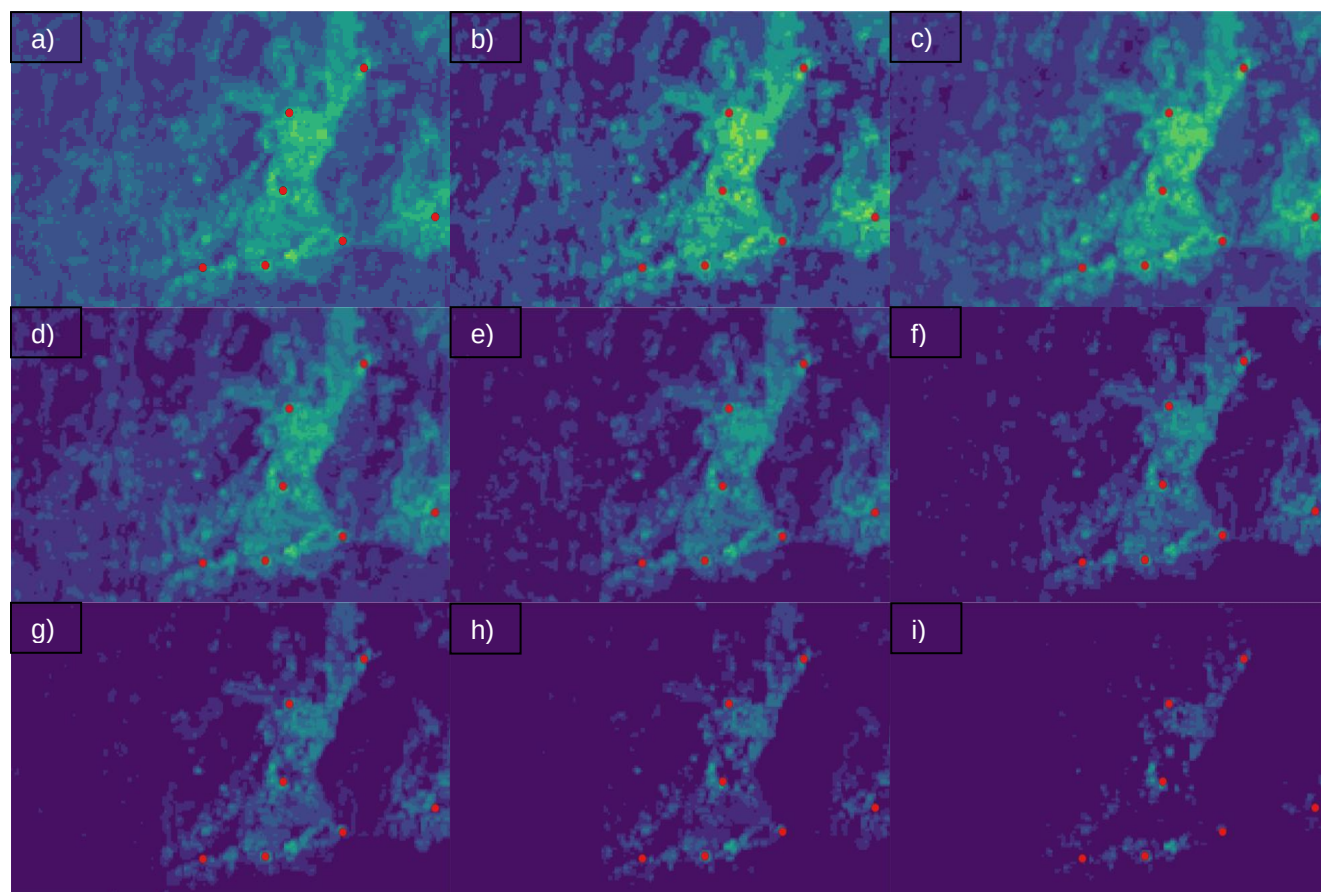


Figure 6. The heatmaps produced by stacking the decisions from the developed models. a) is created by assigning a similar weight for all the normalized outputs coming from all the models. b) ignores the values of the most optimistic and the most pessimistic value for each pixel. c) ignores the 2 most optimistic and the 2 most pessimistic value for each pixel. The rest of the heatmaps are gradually being conservative in their prediction as they ignore d) 20%, e) 40%, f) 50%, g) 60%, h) 70%, and i) 80% of the highest prediction for each pixel/area. The color scheme and legend are consistent with Figure 5.

The developed models are capable of surveying an area measuring 150 km in length and 90 km in width in just under one hour with low to medium computing resources. With this rate an entire state like Nevada which has the highest geothermal activity can be entirely surveyed in less than 21 hours. High graded locations can and should undergo a further seconding exploration phase where domain knowledge is utilized. The constructed tool has been deployed on 3 states in the western US while always comparing them to the locations of geothermal systems (if they exist). Applying the models on different regions of the U.S. with positive results is an indication on the models' scalability and the reproducibility. The results of the models' predictions were also evaluated versus experts' recommendations for these specific areas. The models' predictions showed highly correlated outcomes compared to known locations of geothermal systems as well as experts' recommendations. Furthermore, the models' predictions were evaluated versus the \$/acre for offered sections by BLM in previous lease sales. Again, the models' predictions for areas with high potential correlated to areas with high \$/acre. Furthermore, the models' predictions were able to detect the presence of blind geothermal systems as well as geothermal systems with surface manifestations. The time efficiency and high accuracy of the developed models are very powerful especially in initial geothermal exploration phase, remote areas exploration with little to no data availability, and for exploring vast areas of land like an entire state of a whole country. This tool can be used as a guide for exploration teams to lead them in the direction of further investigation areas and field or ground exploration.

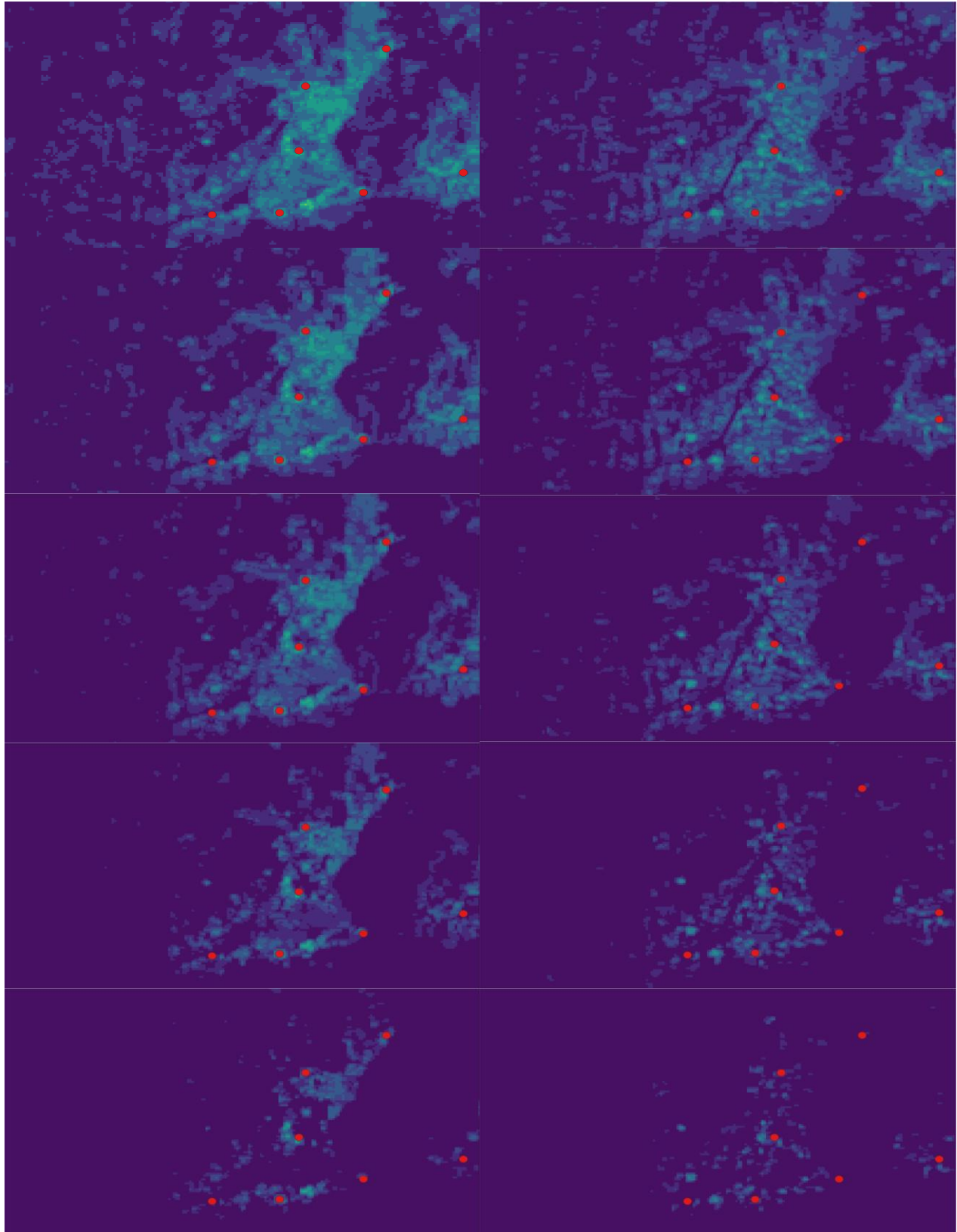


Figure 7. Left column is the stacked models' predictions after dimensionality reduction while the right column is the stacked models' predictions before dimensionality reduction. The level of confidence increases from top to bottom similar to the illustration of Figure 6. The color scheme and legend are consistent with Figure 5.

Conclusions

This framework represents a scalable, adaptable, and impactful solution for geothermal exploration to accelerate clean energy development and enhance decision-making in the industry sector. In the shed of the presented work, we can draw the following conclusions:

- A hybrid AI tool was developed that combines machine learning algorithms and computer vision to identify geothermal prospects.
- The models were trained on approximately 650,000 data points and validated against real-world lease sales data and expert assessments.
- The system demonstrated over 90% accuracy in identifying geothermal prospects, including blind systems with no surface manifestations.
- Model outputs were integrated into GIS-ready heatmaps, enabling practical deployment in field operations.
- These models support early-stage screening by helping prioritize high-probability areas and deprioritize lower-potential sites.
- The tool allows exploration teams to reduce time, cost, and risk in early-stage geothermal development. It can also be used for portfolio de-risking and for reevaluating overlooked acreage with new insights.

In summary, the deployment of hybrid AI and machine learning methods for geothermal field exploration has been shown to significantly improve exploration efficiency and success. This offers a compelling path to cut costs, save time, and reduce risk in discovering new geothermal resources.

We encourage industry stakeholders and researchers to adopt these strategies and help transition this innovation from pilot applications to mainstream practice. With continued refinement, support, and collaboration, AI-driven exploration can accelerate the growth of geothermal energy—unlocking more clean energy resources and enabling smarter, data-informed decisions in the field.

The insights and methodologies presented here provide a strong foundation for future progress, highlighting an exciting intersection of technology and geoscience that stands to benefit both the geothermal industry and the academic community pursuing sustainable energy solutions.

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