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(54) **FACILITATING HYDROCARBON EXPLORATION AND EXTRACTION BY APPLYING A MACHINE-LEARNING MODEL TO SEISMIC DATA**

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(58) **Field of Classification Search**
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See application file for complete search history.

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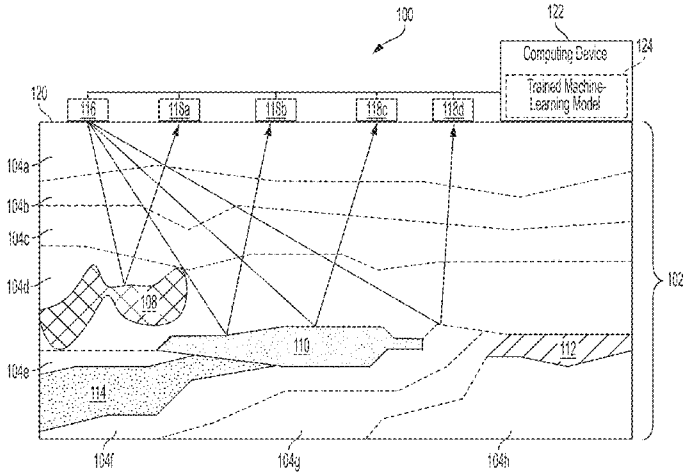
(74) *Attorney, Agent, or Firm* — Kilpatrick Townsend & Stockton LLP

(57) **ABSTRACT**

Hydrocarbon exploration and extraction can be facilitated using machine-learning models. For example, a system described herein can receive seismic data indicating locations of geological bodies in a target area of a subterranean formation. The system can provide the seismic data as input to a trained machine-learning model for determining whether the target area of the subterranean formation includes one or more types of geological bodies. The system can receive an output from the trained machine-learning model indicating whether or not the target area of the subterranean formation includes the one or more types of geological bodies. The system can then execute one or more processing operations for facilitating hydrocarbon exploration or extraction based on the seismic data and the output from the trained machine-learning model.

20 Claims, 7 Drawing Sheets



(51) **Int. Cl.**

G01V 1/30	(2006.01)
G01V 1/34	(2006.01)
G06N 20/00	(2019.01)
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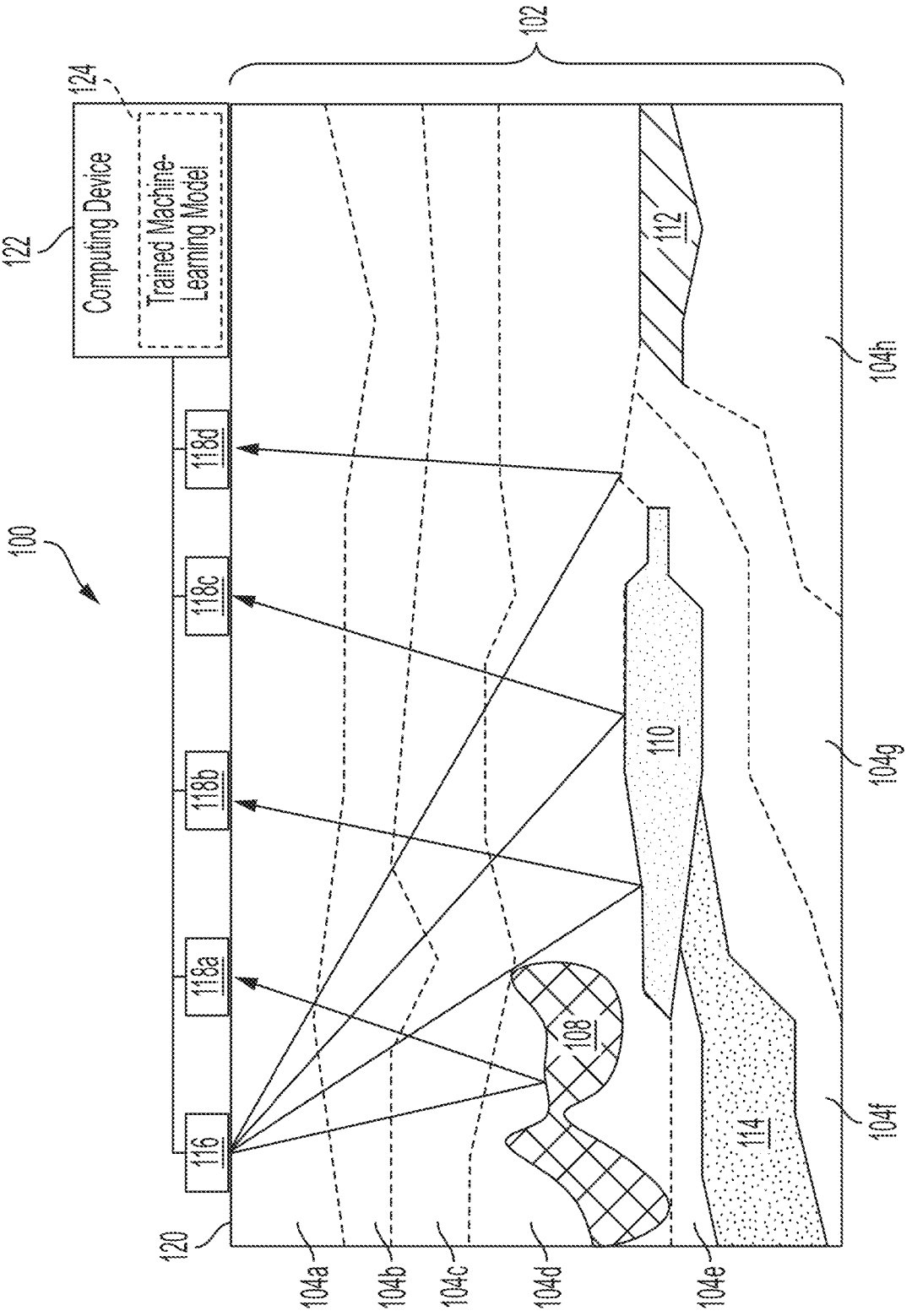
100
102
122
124
Computing Device
Trained Machine-Learning Model
116
118a
118b
118c
118d
120
104a
104b
104c
104d
104e
104f
104g
104h
108
110
112
114

FIG. 1

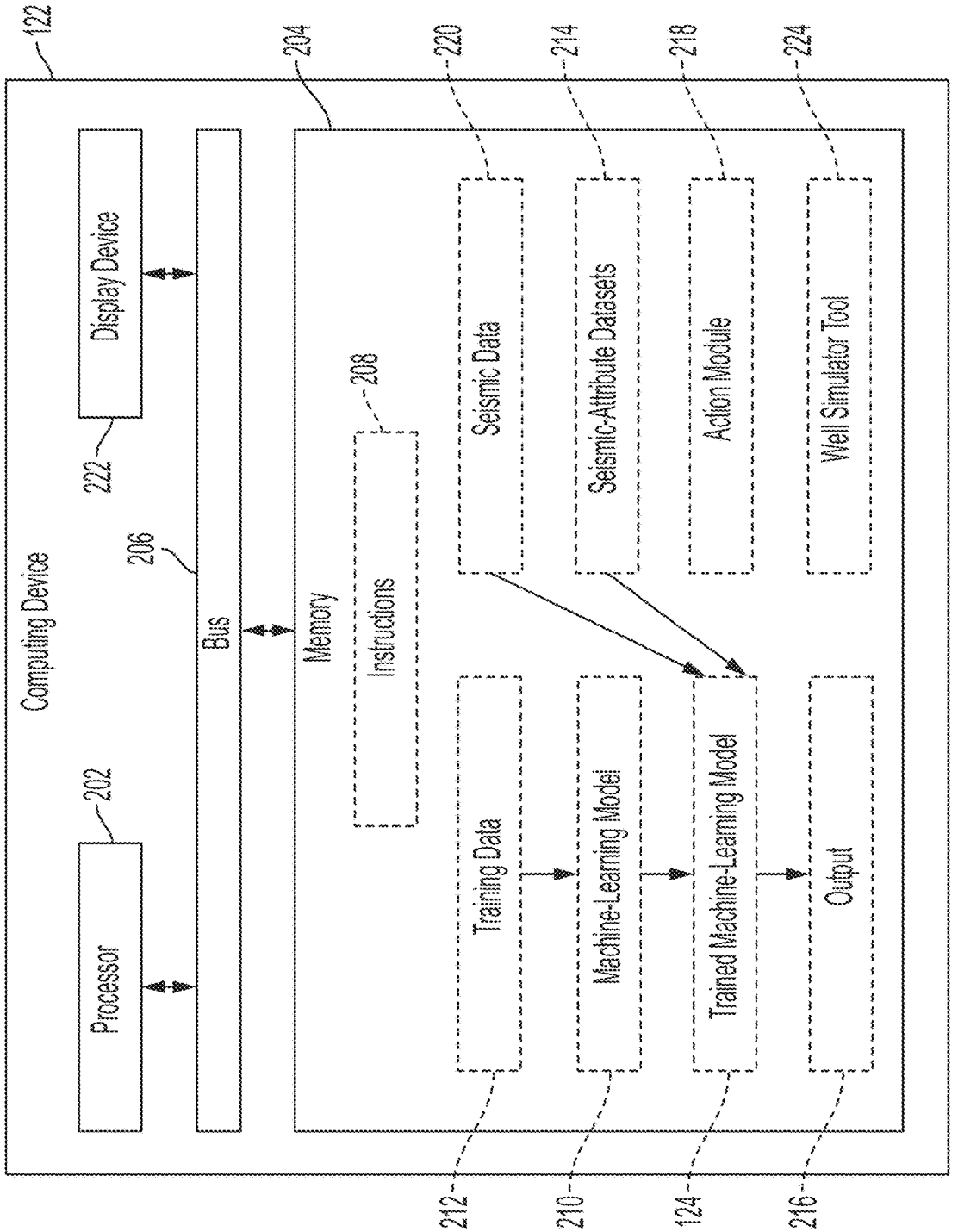
122
Computing Device
Processor
202
Display Device
222
206
Bus
204
Memory
208
Instructions
220
Seismic Data
214
Seismic-Attribute Datasets
218
Action Module
224
Well Simulator Tool
Training Data
Machine-Learning Model
Trained Machine-Learning Model
Output
212
210
124
216

FIG. 2

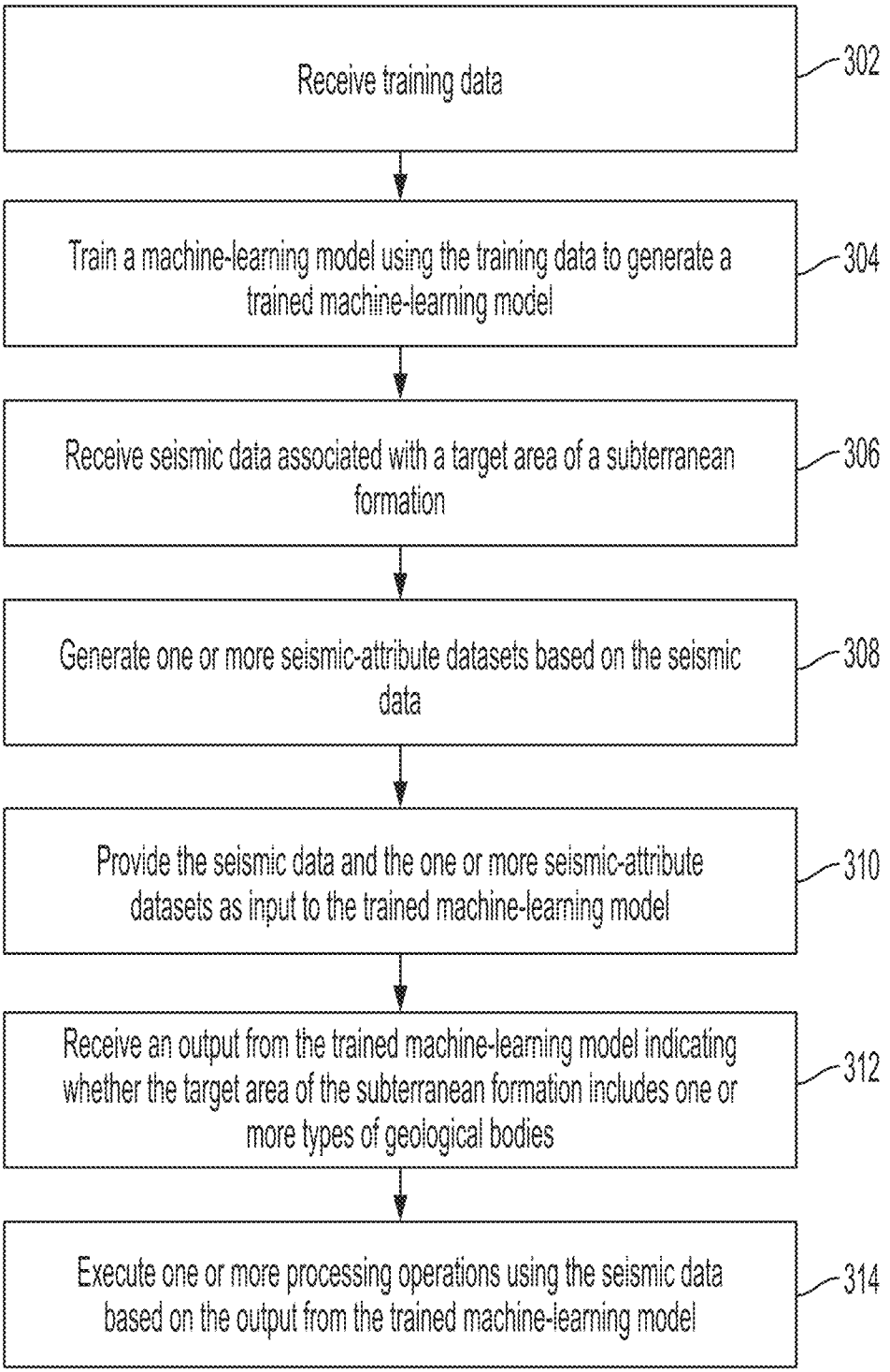
Receive training data
302
Train a machine-learning model using the training data to generate a trained machine-learning model
304
Receive seismic data associated with a target area of a subterranean formation
306
Generate one or more seismic-attribute datasets based on the seismic data
308
Provide the seismic data and the one or more seismic-attribute datasets as input to the trained machine-learning model
310
Receive an output from the trained machine-learning model indicating whether the target area of the subterranean formation includes one or more types of geological bodies
312
Execute one or more processing operations using the seismic data based on the output from the trained machine-learning model
314

FIG. 3

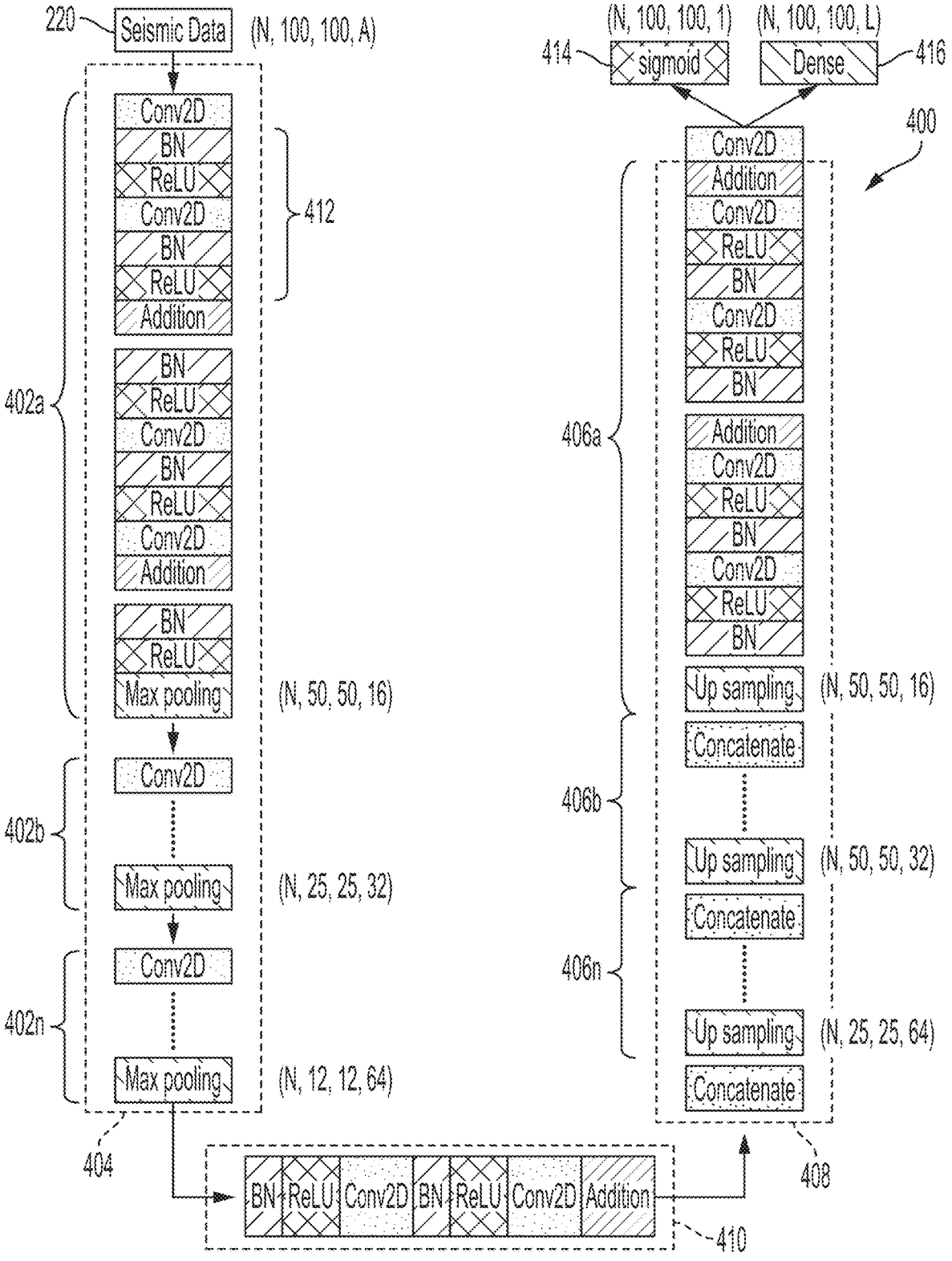
220
Seismic Data
(N, 100, 100, A)
Conv2D
BN
ReLU
Conv2D
BN
ReLU
Addition
412
402a
BN
ReLU
Conv2D
BN
ReLU
Conv2D
Addition
BN
ReLU
Max pooling
(N, 50, 50, 16)
402b
Conv2D
Max pooling
(N, 25, 25, 32)
402n
Conv2D
Max pooling
(N, 12, 12, 64)
404
BN
ReLU
Conv2D
BN
ReLU
Conv2D
Addition
410
(N, 100, 100, 1)
414
sigmoid
(N, 100, 100, L)
Dense
416
400
Conv2D
Addition
Conv2D
ReLU
BN
Conv2D
ReLU
BN
406a
Addition
Conv2D
ReLU
BN
Conv2D
ReLU
BN
Up sampling
(N, 50, 50, 16)
Concatenate
406b
Up sampling
(N, 50, 50, 32)
Concatenate
406n
Up sampling
(N, 25, 25, 64)
Concatenate
408

FIG. 4

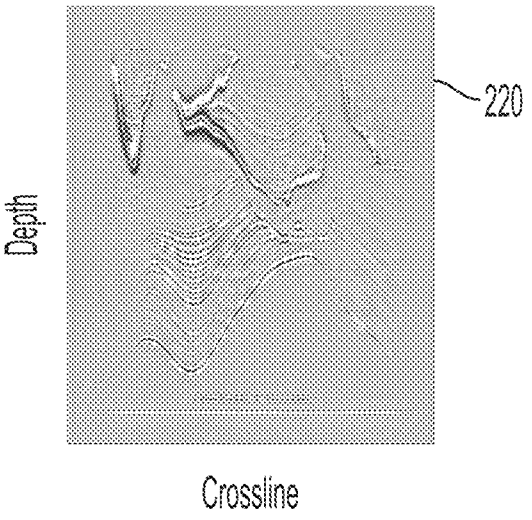

FIG. 5

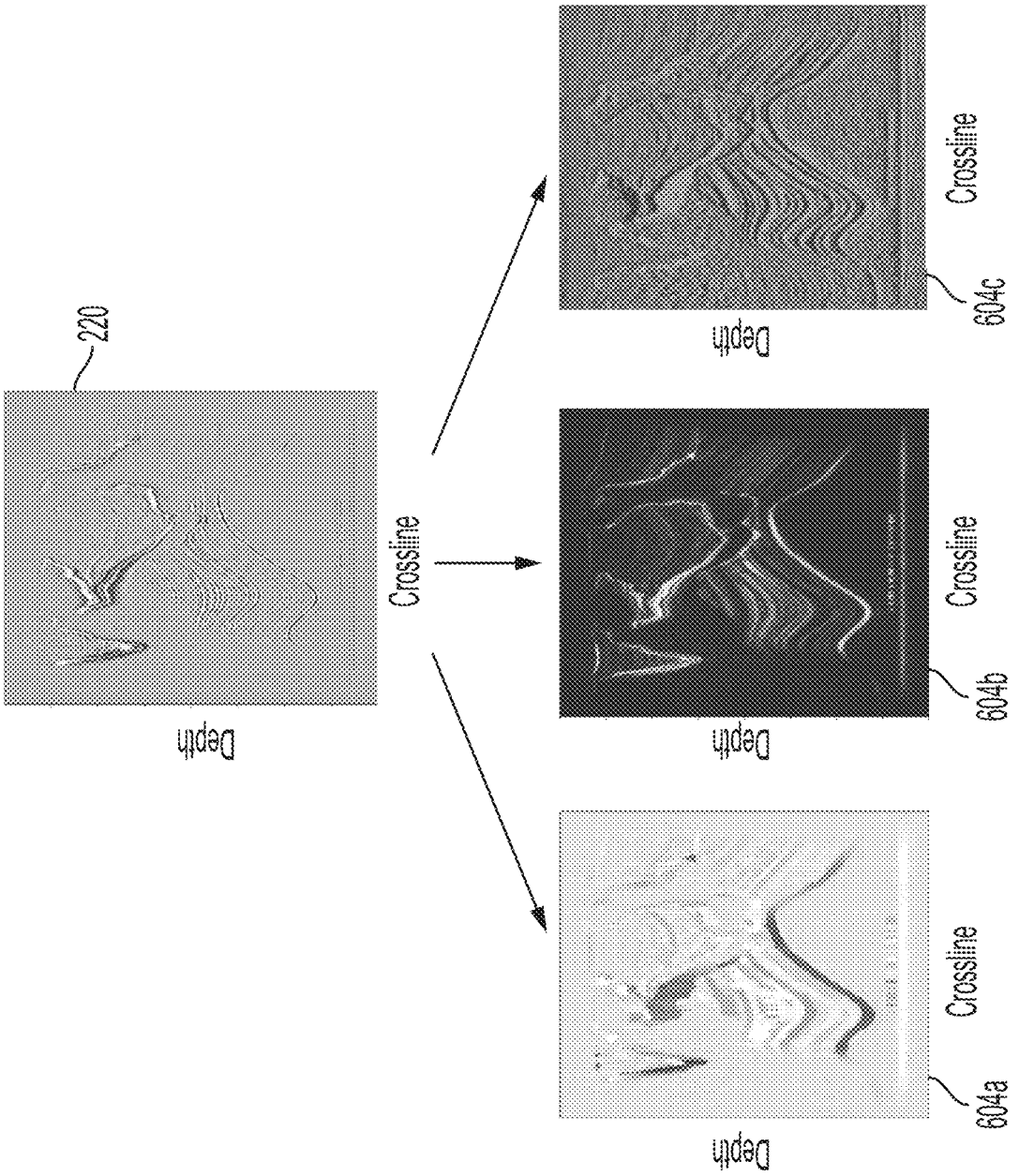
220
Depth
Crossline
Crossline
604c
Depth
Crossline
604b
Depth
Crossline
604a
Depth

FIG. 6

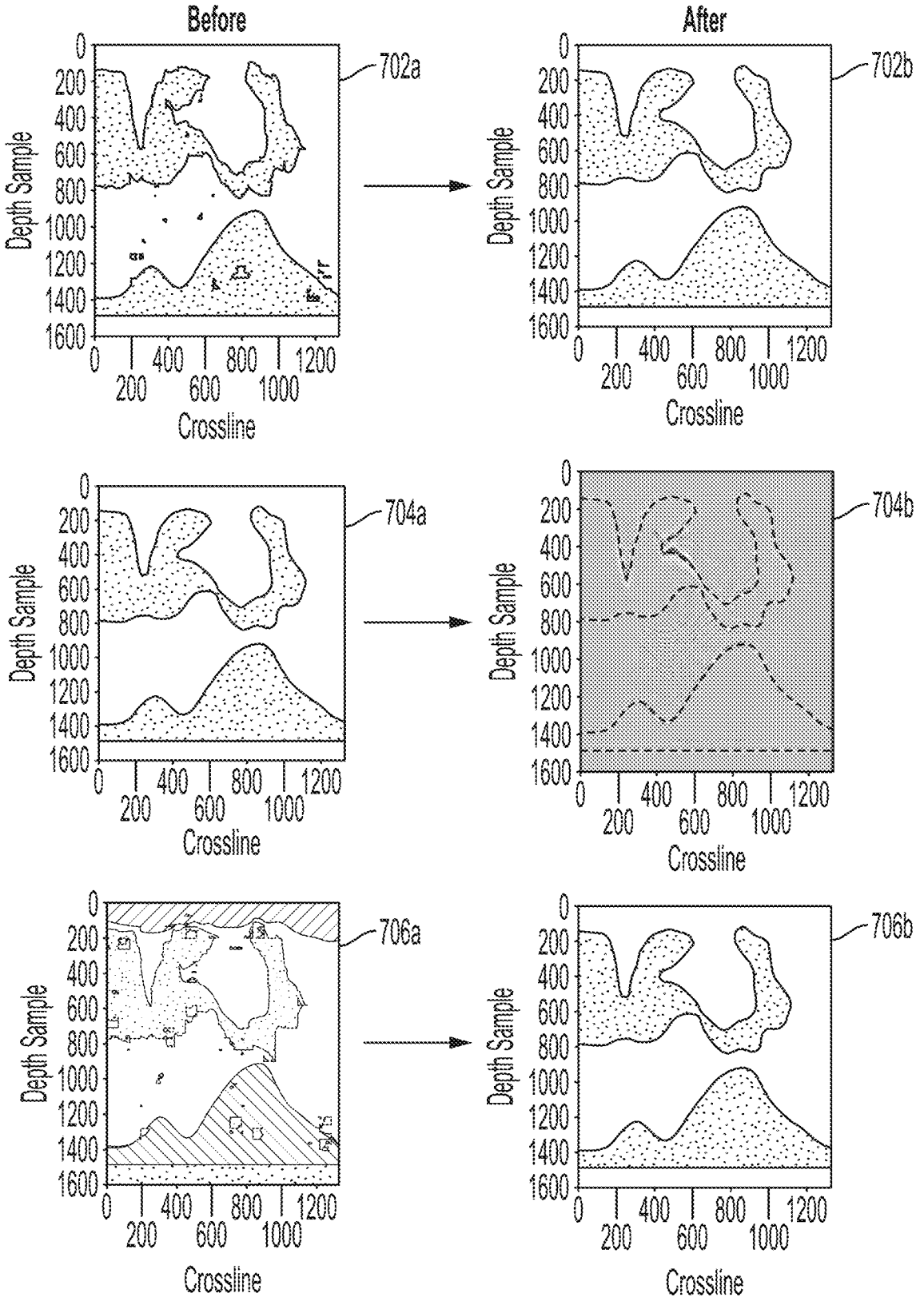
Before
After
702a
702b
704a
704b
706a
706b
Depth Sample
Crossline
0
200
400
600
800
1000
1200
1400
1600

FIG. 7

FACILITATING HYDROCARBON EXPLORATION AND EXTRACTION BY APPLYING A MACHINE-LEARNING MODEL TO SEISMIC DATA

TECHNICAL FIELD

The present disclosure relates generally to hydrocarbon exploration and extraction. More specifically, but not by way of limitation, this disclosure relates to facilitating hydrocarbon exploration or extraction by applying a machine-learning model to seismic data.

BACKGROUND

Hydrocarbon exploration is the search for hydrocarbons (e.g., oil or gas) within a subterranean formation. The search for hydrocarbons relies heavily on the chemical and physical properties of subterranean formations. Well operators can use a variety of tools to measure the chemical and physical properties of the subterranean formation. These measurements can then be interpreted to determine if a subterranean formation has hydrocarbons. The measurements can also be interpreted to determine if a subterranean formation is stable enough to sustain hydrocarbon-extraction operations, such as drilling, completion, and production. Incorrect interpretation of such measurements can result in poor hydrocarbon production and, in some cases, catastrophic wellbore failures.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** depicts an example of an environment including a system for facilitating hydrocarbon exploration and extraction according to some aspects of the present disclosure.

FIG. **2** depicts a block diagram of an example of a computing device according to some aspects of the present disclosure.

FIG. **3** depicts a flow chart of an example of a process according to some aspects of the present disclosure.

FIG. **4** depicts an example of a machine-learning model according to some aspects of the present disclosure.

FIG. **5** depicts an example of seismic data according to some aspects of the present disclosure.

FIG. **6** depicts examples of seismic-attribute datasets according to some aspects of the present disclosure.

FIG. **7** depicts examples of processing operations according to some aspects.

DETAILED DESCRIPTION

Certain aspects and features of the present disclosure relate to facilitating hydrocarbon exploration or extraction by applying a machine-learning model to seismic data. Seismic data is multidimensional data generated using principles of seismology that indicates the physical properties of a subsurface formation. As one particular example, a machine-learning model can receive input including seismic data characterizing a target area of a subterranean formation. In response to receiving the seismic data, the machine-learning model can generate an output indicating what types of geological bodes are present in the target area. A geological body is a geological substance other than rock that is present in a subterranean formation. Exemplary types of geological bodies can include sand bodies, salt bodies, water bodies, gas bodies, and oil bodies. The output of the machine-learning model can be used to determine whether

the target area contains hydrocarbons and is stable enough to sustain hydrocarbon-extraction operations.

The machine-learning model can be trained using a training dataset. The training dataset can include seismic datasets collected from various geographical regions for subterranean formations made of different rock types and geological bodies. Each of the seismic datasets can be assigned one or more labels in the training dataset indicating the type or types of geological bodies that are reflected in the seismic datasets. A supervised training method can be applied to train the machine-learning model based on the training dataset.

In some examples, a computing device can execute (e.g., automatically execute) one or more processing operations based on the output of the machine-learning model. For example, the computing device can determine that a target type of geological body is present in a target area of a subterranean formation based on the output from the machine-learning model. An example of the target type of geological body can be a salt body. The computing device can then apply an image-analysis algorithm to the input seismic data to determine an outer boundary of the target type of geological body in the seismic data. Examples of the image-analysis algorithm can include a smoothing algorithm, an edge-detection algorithm, a segmentation algorithm, or any combination of these. After determining the outer boundary, the computing device can generate a graphical user interface (GUI) that highlights the outer boundary relative to a remainder of the seismic data. For example, the computing device can generate a GUI that overlays an outline of the outer boundary on top of the seismic data. As another example, the computing device can generate a GUI in which seismic content external to the outer boundary is removed from the seismic data. Highlighting the outer boundary can assist the well planner in understanding the seismic data to facilitate wellbore planning and hydrocarbon extraction.

Additionally or alternatively, the one or more processing operations can involve generating a three-dimensional (3D) simulation based on the input seismic data and the output from the machine-learning model. The computing device can execute the 3D simulation to determine simulated properties of the target area of the subterranean formation. The computing device can then provide the simulated properties to the well planner, for example, as part of a GUI. The simulated properties can assist the well planner with anticipating potential problems in performing hydrocarbon-extraction operations in the target area, so that the problems can be avoided or mitigated.

These illustrative examples are given to introduce the reader to the general subject matter discussed here and are not intended to limit the scope of the disclosed concepts. The following sections describe various additional features and examples with reference to the drawings in which like numerals indicate like elements, and directional descriptions are used to describe the illustrative aspects but, like the illustrative aspects, should not be used to limit the present disclosure.

FIG. **1** is an example of an environment **100** that includes a system for facilitating hydrocarbon exploration and extraction according to some aspects of the present disclosure. The environment **100** includes a subterranean formation **102** formed from various earth strata **104***a-h*. The subterranean formation **102** includes various geological bodies, such as a salt body **108** containing salt, an oil body **110** containing oil, a gas body **112** containing gas, and a water body **114**

containing water. Other examples may include more, fewer, or different types of earth strata and geological bodies.

At least a portion of the system can be positioned at the surface **120** of the subterranean formation **102** for detecting geological bodies in the subterranean formation **102**. For example, the system can include a signal source **116** and sensors **118***a-d*. Examples of the signal source **116** can include a vibration unit or an explosive charge, and examples of the sensors **118***a-d* can include geophones or hydrophones. The signal source **116** can emit one or more waves into a target area of the subterranean formation **102**. In the example shown in FIG. **1**, the waves are represented by black arrows and the target area is the portion of the subterranean formation **102** positioned below sensors **118***a-d*. The waves can reflect off the geological bodies and return to the sensors **118***a-d*, which can detect the reflected waves and provide corresponding sensor data to a computing device **122**, which may also form part of the system.

As one particular example, the signal source **116** can include a vibration unit and the sensors **118***a-d* can include geophones. The vibration unit can emit vibrations that propagate through the target area of the subterranean formation **102**, reflect off the geological bodies, and return to the geophones. The geophones can receive the reflected vibrations and generate seismic data based on the reflected vibrations. An example of the seismic data can be a seismic trace. The geophones can then transmit their respective seismic data to the computing device **122**.

The computing device **122** includes a trained machine-learning model **124** that can receive seismic data as input and provide an output indicating which types of geological bodies are present in the target area of the subterranean formation **102**. For example, the computing device **122** can execute the trained machine-learning model **124** based on the seismic data to generate an output indicating whether or not the target area includes a salt body **108**, an oil body **110**, a gas body **112**, a water body **114**, a volcanic intrusion, a certain type of rock layer, or any combination of these. This can provide useful information to a well operator as to whether the target area is suitable for hydrocarbon extraction. For example, the presence of the salt body **108** may make the target area unstable and therefore poorly suited to drilling operations. Notifying the well operator of this information before he initiates drilling, completion, or extraction operations can minimize the likelihood of costly and dangerous events, such as casing fracturing and wellbore collapse.

While FIG. **1** depicts an exemplary system that includes certain components (e.g., the signal source **116**, sensors **118***a-d*, and computing device **122**), this is intended to be illustrative and non-limiting. Other examples may include more, fewer, or different components. For instance, another example may involve the computing device **122** receiving seismic data from a remote computing device via a network, such as the Internet. The computing device **122** can receive the seismic data from the remote computing device additionally or alternatively to receiving seismic data from the sensors **118***a-d*. And in some examples, the computing device **122** may be positioned offsite, rather than proximately to the target area of the subterranean formation **102**.

FIG. **2** is a block diagram of an example of the computing device **122** according to some aspects of the present disclosure. While FIG. **2** depicts the computing device **122** as including certain components, other examples may involve more, fewer, or different components than are shown in FIG. **2**.

As shown, the computing device **122** includes a processor **202** communicatively coupled to a memory **204** by a bus **206**. The processor **202** can include one processor or multiple processors. Non-limiting examples of the processor **202** include a Field-Programmable Gate Array (FPGA), an application-specific integrated circuit (ASIC), a microprocessor, or any combination of these. The processor **202** can execute instructions **208** stored in the memory **204** to perform operations. In some examples, the instructions **208** can include processor-specific instructions generated by a compiler or an interpreter from code written in any suitable computer-programming language, such as C, C++, C #, or Java.

The memory **204** can include one memory device or multiple memory devices. The memory **204** can be non-volatile and may include any type of memory device that retains stored information when powered off. Non-limiting examples of the memory **204** include electrically erasable and programmable read-only memory (EEPROM), flash memory, or any other type of non-volatile memory. At least some of the memory device includes a non-transitory computer-readable medium from which the processor **202** can read instructions **208**. A non-transitory computer-readable medium can include electronic, optical, magnetic, or other storage devices capable of providing the processor **202** with the instructions **208** or other program code. Non-limiting examples of a non-transitory computer-readable medium include magnetic disk(s), memory chip(s), ROM, random-access memory (RAM), an ASIC, a configured processor, optical storage, or any other medium from which a computer processor can read the instructions **208**.

Additionally, the computing device **122** can include training data **212** for training a machine-learning model **210**. The training data **212** can include multiple input-output pairs. Each input-output pair includes, as input, a seismic dataset characterizing a subterranean formation area. A subterranean formation area is a designated area of a subterranean formation. Each input-output pair also includes, as output, one or more output labels specifying one or more types of geological bodies present in that subterranean formation area. For example, an input-output pair can include an input seismic trace corresponding to a subterranean formation area and one or more output labels indicating that the subterranean formation area includes a salt body and a gas body. The output labels may have been manually assigned to the input seismic dataset by a geologist or other expert. The training data **212** can include any number and combination of input-output pairs corresponding to any number and combination of subterranean formation areas, though more input-output pairs may produce better training results.

In some examples, the machine-learning model **210** can include a neural network, a support vector machine, a Bayesian classifier, or any combination of these. The machine-learning model **210** may be in an untrained state. The machine-learning model **210** can be trained using the training data **212** to generate a trained machine-learning model **124**.

Once trained, the machine-learning model **124** can be configured to receive seismic data **220** corresponding to a target area of a subterranean formation as input and responsively generate an output **216** indicating one or more types of geological bodies that are present in the target area. A target area of a subterranean formation is a designated area of subterranean formation to be analyzed, for example, to determine whether the area contains one or more types of geological bodies. The seismic data **220** can be different than the training data **212**, such that the seismic data **220** was not

used to train the machine-learning model **210**. In this way, the seismic data **220** can be "unknown" to the trained machine-learning model **124**.

The seismic data **220** is multidimensional data, such as two-dimensional (2D) data or three-dimensional (3D) data. For example, the seismic data **220** can include data points having multiple dimensions, such as amplitude, depth, and time. The data points can have the raw data values as originally provided by the sensors, or the data points can have derived values generated by pre-processing the raw data values. An example of the seismic data **220** is depicted in FIG. **5**. In FIG. **5**, the X-axis represents crossline number (e.g., in kilometers) and the Y-axis represents depth. A crossline is a seismic line within a 3D survey that is perpendicular to the direction in which the data was acquired.

In some examples, the computing device **122** can also determine one or more seismic-attribute datasets **214** based on the seismic data **220**. A seismic-attribute dataset is a multidimensional dataset including values for a particular type of seismic attribute, such as a relative acoustic impedance, apparent polarity, reflection strength, root mean squared (RMS) frequency, or an arc length. The computing device **122** can determine the seismic-attribute datasets **214** prior to providing the seismic data **220** as input to the trained machine-learning model **124**, and then provide the seismic-attribute datasets **214** as input to the trained machine-learning model **124** in addition to the seismic data **220**. The seismic-attribute datasets **214** can assist the trained machine-learning model **124** in determining which types of geological bodies are present in the target area of the subterranean formation. For example, the seismic-attribute datasets **214** can serve as additional contextual information that can improve the accuracy of the output **216** from the trained machine-learning model **124**.

The computing device **122** can also include an action module **218**. The action module **218** can include executable program code for taking one or more actions based on the output **216** of the trained machine-learning model **124**. For example, the computing device **122** can execute the action module **218** to determine whether the target area of the subterranean formation is suitable for drilling a wellbore based on the output **216** from the trained machine-learning model **124**. The computing device **122** can then generate a graphical user interface (GUI) indicating whether the target area is suitable for drilling and display the GUI on a display device **222**, such as a liquid crystal display or light emitting diode display.

As one particular example, the computing device **122** use the trained machine-learning model **124** to generate an output **216** indicating that a target area of the subterranean formation associated with the seismic data **220** includes a particular type of geological body, such as a water body or salt body. The computing device **122** can then execute the action module **218** to apply a set of rules based on the output **216** to determine whether the target area is suitable for drilling. The rules may indicate that a presence of the particular type of geological body renders the target area unsuitable for drilling. So, the computing device **122** can generate and display a GUI that includes an alert indicating that the target area is unsuitable for drilling. As an alternative example, the computing device **122** use the trained machine-learning model **124** to generate an output **216** indicating that a target area of the subterranean formation associated with the seismic data **220** includes a first type of geological body, such as a gas body, and lacks a second type of geological body, such as a water body or salt body. The computing device **122** can then execute the action module **218** to apply the set of rules based on the output **216** to determine whether the target area is suitable for drilling. The rules may indicate that a presence of the first body and the absence of the second body renders the target area of the subterranean formation suitable for drilling. So, the computing device **122** can generate and display a GUI that includes a notification indicating that the target area is suitable for drilling.

As another example, the computing device **122** use the trained machine-learning model **124** to determine that a target area of the subterranean formation associated with the seismic data **220** includes particular type of geological body, such as a water body or salt body. The computing device **122** can then execute the action module **218** to convey the seismic data **220**, the output **216**, or both of these to a well simulator tool **224**, such as DecisionSpace® 365 by Halliburton Company. The well simulator tool **224** can receive the seismic data **220** and the output **216** and responsively generate a three-dimensional (3D) simulation of the target area of the subterranean formation. The output **216** can provide context to the simulation that improves the accuracy of the 3D simulation. For example, the well simulator tool **224** may be unable to unilaterally determine whether the target area of the subterranean formation includes certain types of geological bodies, but that information may be useful for generating an accurate simulation. Thus, by providing the output **216** to the well simulator tool **224**, the well simulator tool **224** can produce more accurate simulation results. After generating the 3D simulation, the well simulator tool **224** can execute the 3D simulation to determine simulated properties of the target area of the subterranean formation. The well simulator tool **224** can then provide the simulated properties to a well planner, who can use the simulated properties in one or more hydrocarbon exploration or extraction processes.

In some examples, the computing device **122** can implement the process shown in FIG. **3** for effectuating some aspects of the present disclosure. Other examples can involve more operations, fewer operations, different operations, or a different order of the operations shown in FIG. **3**. The operations of FIG. **3** are described below with reference to the components shown in FIG. **2**.

In block **302**, a processor **202** receives training data **212**. The training data **212** can include a plurality of seismic datasets and their corresponding output labels. For example, the training data **212** can include a plurality of seismic datasets and corresponding indicators of which of type(s) of geological bodies are present in each seismic dataset among the plurality of seismic datasets.

In block **304**, the processor **202** trains a machine-learning model **210** using the training data **212** to generate a trained machine-learning model **124**. The processor **202** can train the machine-learning model **210** using a supervised training approach, through which the machine-learning model **210** can learn patterns within the training data **212** (e.g., patterns between the input seismic datasets and the output labels). The processor **202** can train the machine-learning model **210** by iteratively tuning weights internal to the machine-learning model **210** based on the training data **212**.

One example of a machine-learning model **400** (e.g., the trained machine-learning model **124**) suitable for implementing some aspects of the present disclosure is shown in FIG. **4**. The machine-learning model **400** can include a plurality of encoding layer groups **402***a-n* that collectively form an encoding portion **404** of the machine-learning model **400**. Each of the encoding layer groups **402***a-n* can include the layers shown in FIG. **4**, as arranged in the order

shown in FIG. **4**. Though, other combinations and arrangements of layers are possible and contemplated within the scope of this disclosure. The output from each layer feeds into the next layer. In other words, the output of each layer serves as an input for the next layer.

As shown in FIG. **4**, the encoding layer groups **402***a-n* can include two-dimensional convolutional layers (Conv2D). A Conv2D layer performs two-dimensional convolution on its input to extract patterns or features from the input. The encoding layer groups **402***a-n* may also include batch normalization (BN) layers. A BN layer normalizes its input in batches. BN layers can improve the speed, performance, and stability of the machine-learning model **400**. The encoding layer groups **402***a-n* may also include rectified linear unit (ReLU) layers. A ReLU layer is an activation layer that applies a rectifier to its input. ReLU layers can be trained faster using backpropagation than other types of activation layers.

In some examples, the encoding layer groups **402***a-n* can also include addition layers (Addition). An Addition layer sums together a first coefficient of a Conv2D layer with a second coefficient of multiple layers **412** in an encoding layer group **402***a*. These coefficients can be tuned during the training process for the machine-learning model **400**. In the example shown in FIG. **4**, the multiple layers of the encoding layer group **402***a* include a BN layer, a ReLU layer, a Conv2D layer, and another ReLU layer. But other examples can involve more, fewer, or different layers. The Addition layer can assist with avoiding a vanishing gradient problem in which the gradient of the machine-learning model **400** diminishes to approximately zero (vanishing). Such a vanishing gradient can prevent the machine-learning model **400** from further learning and reduce the accuracy of the machine-learning model **400**. Thus, avoiding the vanishing gradient can improve the accuracy of the machine-learning model **400**.

The encoding layer groups **402***a-n* may also include max pooling layers (Max pooling). A max pooling layer can downsample its input to reduce the size of the input. For example, a max pooling layer can reduce a 100×100 matrix of values to a 50×50 matrix of values. This downsampling can reduce the total number of computations performed by the machine-learning model **400** and increase efficiency.

A plurality of decoding layer groups **406***a-n* can also be included in the machine-learning model **400**. The plurality of decoding layer groups **406***a-n* can collectively form a decoding portion **408** of the machine-learning model **400**. Each of the decoding layer groups **406***a-n* can include the layers shown in FIG. **4**, as arranged in the order shown in FIG. **4**. Though, other combinations and arrangements of layers are possible and contemplated within the scope of this disclosure. The output from each layer feeds into the next layer. In other words, the output of each layer serves as an input for the next layer.

The decoding layer groups **406***a-n* can include Conv2D layers, BN layers, ReLU layers, Addition layers, upsampling layers (Upsampling), concatenation layers (Concatenate), or any combination of these. The Conv2D layers, BN layers, ReLU layers, and Addition layers can function similarly to those described above. An upsampling layer can generally perform the opposite functionality to the maxpooling layers and increase the size of an input. For example, the upsampling layer can upsample its input from a 50×50 matrix of values to a 100×100 matrix of values. A concatenation layer can perform an assembly process that ensures that the output size of a related upsampling layer matches the output size of a maxpooling layer corresponding to the upsampling layer. For example, the concatenation layer in decoding layer group **406***b* can ensure that the output size (50×50) of the upsampling layer in that decoding layer group **406***b* matches the maxpooling output size from the encoding layer group **402***a*. And the concatenation layer in decoding layer group **406***n* can ensure that the output size (25×25) of the upsampling layer in that decoding layer group **406***n* matches the maxpooling output size from the encoding layer **402***b*. And so on.

A bridge portion **410** can connect the encoding portion **404** to the decoding portion **408**. In the example shown in FIG. **4**, the bridge portion **410** includes BN layers, ReLU layers, Conv2D layers, and an addition layer. But other examples may involve more layers, fewer layers, different layers, or a different arrangement of layers than is shown.

In some examples, the machine-learning model **400** can further include (e.g., terminate with) a sigmoid layer **414**. The sigmoid layer **414** can provide a numerical value between zero and one indicating a likelihood that a target area of a subterranean formation associated with the input seismic data **220** has a particular type of geological body. For example, the sigmoid layer **414** can output a numerical value of 0.78 if the machine-learning model determines that there is a 78% probability that the target area has a salt body. As another example, the sigmoid layer **414** can output a numerical value of 0.32 if the machine-learning model determines that there is a 32% probability that the target area has a salt body.

The machine-learning model **400** can additionally or alternatively include a dense layer **416**. The dense layer **416** can provide one or more identifiers (e.g., labels or integer values) indicating one or more types of geological bodies that are present in the target area of the subterranean formation. For example, the dense layer can output **1** for a salt body, **2** for a water body, **3** for a gas body, **4** for an oil body, or any combination of these. But other numerical schemes are possible.

To assist with understanding the machine-learning model **400**, FIG. **4** depicts information in the format (N, X, Y, A) next to each of the encoding layer groups **402***a-n* and decoding layer groups **406***a-n*. N is the number of samples in the input seismic data **220**, where N is in a matrix format; X is the number of rows in the matrix; Y is the number of columns in the matrix; and A is the number of channels associated with that layer group. For example, A can be the number of seismic attributes (e.g., apparent polarity, arc length, and relative amplitude change) derived from the input seismic data **220** that can be analyzed by the layer group. The machine-learning model **400** can accept any number and combination of channels. FIG. **4** also depicts information in the format (N, X, Y, L) next to the sigmoid layer **414** and the dense layer **416**. N, X, and Y are the same as above, while L is the number of outputs produced by the layer. Since the sigmoid layer **414** produces a single output value, the sigmoid layer **414** has an L value of 1. And since the dense layer **416** can provide L output labels, the dense layer **416** has a value of L.

The machine-learning model architecture shown in FIG. **4** is exemplary and intended to be non-limiting. In other examples, the machine-learning model **400** may have more layers, fewer layers, different layers, or a different arrangement of layers than is shown in FIG. **4**. For instance, other examples may lack the BN layers, Addition layers, concatenate layers, or any combination of these. The values for N, X, Y, A, and L are also exemplary and intended to be non-limiting. Other examples may have different values for N, X, Y, A, and L than is shown in FIG. **4**.

Returning to FIG. **3**, after the machine-learning model **124** is trained, the process can continue to block **306**. At block **306**, the processor **202** receives seismic data **220** associated with a target area of a subterranean formation. The seismic data **220** can be generated using one or more sensors, such as one or more geophones or hydrophones, positioned proximate to the target area of the subterranean formation.

The seismic data **220** can be provided in any suitable format, such as a SEG-Y file format. The SEG-Y format is a standard format developed by the Society of Exploration Geophysicists (SEG) for storing geophysical data. The trained machine-learning model **124** can be configured to accept and process data in a particular file format, such as SEG-Y, to produce an output **216**.

In block **308**, the processor **202** generates one or more seismic-attribute datasets **214** based on the seismic data **220**, where the one or more seismic-attribute datasets **214** correspond to one or more types of seismic attributes. The processor **202** can apply one or more algorithms to the seismic data **220** to generate the seismic-attribute datasets **214**.

One exemplary type of seismic attribute is apparent polarity. Apparent polarity can be the polarity of seismic data scaled by the reflection strength, which roughly approximates scaled reflection coefficients. Apparent polarity can be a wavelet-response attribute, like response phase and response frequency. In an interval of seismic data **220** that is bound by consecutive envelope troughs (e.g., reflection strength minima), the apparent polarity can be the sign of the seismic data **220** measured at the envelope peak multiplied by the value of the envelope peak, and held constant in the interval.

Another exemplary type of seismic attribute is arc length. Arc length can be the length of the seismic waveform in a window measured along its curves divided by the length of the window. Arc length increases with both amplitude and frequency. Thus, a higher arc length may indicate strongly reflecting and moderately spaced bedding, or moderately reflecting and thinly spaced bedding. However, arc length tends to be driven more by amplitude than by frequency, so that it resembles RMS amplitude and other amplitude attributes.

Yet another exemplary type of seismic attribute is relative amplitude change. Relative amplitude change can be a directional attribute and appears illuminated along the time axis when displayed in monochrome. Relative amplitude change may reveal structural detail hidden in the amplitudes and highlights zones of reflection interference, which occur at amplitude minima between reflections. Relative amplitude change may blend particularly well with response phase and response frequency, because these attributes have a blocky output that changes values at amplitude minima.

Some examples of seismic-attribute datasets **604***a-c* are shown in FIG. **6**. In FIG. **6**, the X-axes represent crossline number and the Y-axes represent depth. Seismic-attribute dataset **604***a* can indicate apparent polarities associated with the target area of the subterranean formation, seismic-attribute dataset **604***b* can indicate arc lengths associated with the target area, and seismic-attribute dataset **604***c* can indicate relative amplitude changes associated with the target area. But more or different seismic-attribute datasets corresponding to more or different types of seismic attributes can be generated.

Each data point in a seismic-attribute dataset can be generated by applying an algorithm to the value(s) of a related data point in the seismic data **220**, such that each data point in the seismic-attribute dataset is related to a corresponding data point in the seismic data **220**. This can result in the seismic-attribute datasets having the same dimensions as the input seismic data **220**, in some examples. But in other examples, the seismic-attribute datasets can have different dimensions than the input seismic data **220**.

In block **310**, the processor **202** provides the seismic data **220**, the one or more seismic-attribute datasets **214**, or both of these as input to the trained machine-learning model **124**.

In block **312**, the processor **202** receives an output **216** from the trained machine-learning model **124**. The output **216** can indicate whether the target area of the subterranean formation includes one or more types of geological bodies. For example, the output **216** can be a single numerical value from the sigmoid layer **414** of the machine-learning model **400** of FIG. **4**, where the single numerical value indicates a probability of the target area including a target type of geological body. Additionally or alternatively, the output **216** can be one or more identifiers (e.g., integer values) from the dense layer **416** of the machine-learning model **400** of FIG. **4**, where the identifiers indicate one or more types of geological bodies are present in the target area of the subterranean formation.

In block **314**, the processor **202** executes one or more processing operations using the seismic data **220** based on the output **216** from the trained machine-learning model **124**. In some examples, the processor **202** can execute the action module **218** to implement the one or more processing operations. For example, the action module **218** may include program code that is executable by the processor **202** for causing the processor **20** to implement the one or more processing operations.

In some examples, the one or more processing operations can involve smoothing an outer boundary of a target type of geological body in the seismic data **220**. The processor **202** can smooth the outer boundary by applying a smoothing filter, such as a median filter, to the seismic data **220**. One example of such smoothing is depicted in boxes **702***a-b* of FIG. **7**. Box **702***a* depicts an outer boundary of a salt body prior to smoothing. Box **702***b* depicts the outer boundary of the salt body subsequent to smoothing. Smoothing the outer boundary can make the seismic data **220** easier to read and more conducive to further processing.

Additionally or alternatively, the one or more processing operations can involve identifying a boundary of a target type of geological body in the seismic data **220**. In one such example, the processor **202** can determine that the target type of geological body (e.g., a salt body) is present in the target area of the subterranean formation based on the output **216** from the trained machine-learning model. The processor **202** can then execute one or more image-analysis algorithms on the seismic data **220** to determine an outer boundary of the target type of geological body. Examples of the image-analysis algorithms can include a smoothing algorithm, an edge-detection algorithm, a segmentation algorithm, or any combination of these. The processor **202** may then highlight the outer boundary to assist a user in visualizing the outer boundary. For instance, the processor **202** can generate a GUI that highlights the outer boundary within the seismic data **220**. The processor **202** can then display the GUI on a display device **222**.

Two approaches for highlighting the outer boundary of the target geological body are shown in FIG. **7**, though other approaches are possible. One approach involves overlaying an outline of the outer boundary of the target geological body on the seismic data **220**. This approach is represented in boxes **704***a-b*. Box **704***a* depicts an outer boundary of a

salt body identified in the seismic data **220** by the processor **202**. Box **704***b* depicts an outline of the salt body overlaid on the seismic data **220** by the processor **202**, to highlight the outer boundary for the user. Another approach involves removing content external to the outer boundary of the target geological body from the seismic data **220**. This approach is represented in boxes **706***a-b*. Box **706***a* depicts the seismic data **220**, which includes a salt body in this example. Box **706***b* depicts the seismic data **220**, where content external to the outer boundary of the salt body has been removed from the seismic data **220** by the processor **202**. Removing such extraneous content can focus the user's attention on the target geological body (e.g., the salt body in FIG. **7**).

In some examples, the one or more processing operations can additionally or alternatively include the actions described above with regard to FIG. **2**. For example, the processor **202** can determine whether a target area of the subterranean formation is suitable for drilling a wellbore based on the output **216** from the trained machine-learning model **124**. The computing device **122** can then generate a GUI indicating whether the target area is suitable for drilling and display the GUI on the display device **222**. As another example, the processor **202** can generate a 3D simulation based on the seismic data **220** and the output **216** from the trained machine-learning model **124**, execute the 3D simulation to determine simulated properties of the target area of the subterranean formation, and provide the simulated properties to a user (e.g., a well planner).

Hydrocarbon exploration and extraction can be facilitated according to one or more of the following examples.

EXAMPLE #1

A system of the present disclosure can include a processor and a memory including instructions that are executable by the processor. The instructions can be executable for causing the processor to receive seismic data indicating locations of a plurality of geological bodies in a target area of a subterranean formation. The instructions can be executable for causing the processor to provide the seismic data as input to a trained machine-learning model for determining whether the target area of the subterranean formation includes one or more types of geological bodies. The instructions can be executable for causing the processor to, in response to providing the seismic data as input to the trained machine-learning model, receive an output from the trained machine-learning model indicating that the target area of the subterranean formation includes the one or more types of geological bodies. The instructions can be executable for causing the processor to execute one or more processing operations for facilitating hydrocarbon exploration or extraction based on the seismic data and the output from the trained machine-learning model.

EXAMPLE #2

The system of Example #1 may feature the one or more types of geological bodies including a salt body, a water body, or a hydrocarbon body.

EXAMPLE #3

The system of any of Examples #1-2 may feature the one or more processing operations including: determining that a target type of geological body is present in the target area of the subterranean formation based on the output from the trained machine-learning model; executing an edge-detection algorithm on the seismic data to determine an outer boundary of the target type of geological body that is present in the target area; generating a graphical user interface that highlights the outer boundary relative to the seismic data; and displaying the graphical user interface on a display device.

EXAMPLE #4

The system of Example #3 may feature the graphical user interface including an outline of the outer boundary overtop of the seismic data to highlight the outer boundary; or the graphical user interface excluding seismic content external to the outer boundary from the seismic data to highlight the outer boundary.

EXAMPLE #5

The system of any of Examples #1-4 may feature the one or more processing operations including smoothing the seismic data by applying a median filter to the seismic data.

EXAMPLE #6

The system of any of Examples #1-5 may feature the memory further including instructions that are executable by the processor for causing the processor to generate a seismic-attribute dataset based on the seismic data. The seismic-attribute dataset can include a plurality of data point values for a particular type of seismic attribute. Each data point value in the plurality of data point values can be generated by applying one or more algorithms to a corresponding data point in the seismic data. The instructions may also be executable by the processor for causing the processor to provide the seismic-attribute dataset as input to the trained machine-learning model in addition to the seismic data. The seismic-attribute dataset can be used by the trained machine-learning model in conjunction with the seismic data for determining whether the target area of the subterranean formation includes the one or more types of geological bodies.

EXAMPLE #7

The system of Example #6 may feature the particular type of seismic attribute being a relative acoustic impedance, an apparent polarity, a reflection strength, a root mean squared frequency, or an arc length.

EXAMPLE #8

The system of any of Examples #1-7 may feature the memory further including instructions that are executable by the processor for causing the processor to, prior to receiving the seismic data: receive training data that includes a plurality of seismic datasets, where the training data can indicate which of the one or more types of geological bodies are present in each seismic dataset among the plurality of seismic datasets, and where the training data can exclude the seismic data; and train a machine-learning model using the training data to generate the trained machine-learning model.

EXAMPLE #9

The system of any of Examples #1-8 may feature the one or more processing operations including determining that

the target area of the subterranean formation is suitable or unsuitable for drilling a wellbore by applying the output from the trained machine-learning model to a predefined set of rules; generating a graphical user interface indicating that the target area is suitable or unsuitable for drilling the wellbore, respectively; and displaying the graphical user interface on a display device.

EXAMPLE #10

The system of any of Examples #1-9 may feature the one or more processing operations including generating a three-dimensional simulation of the target area of the subterranean formation based on the seismic data and the output from the trained machine-learning model; executing the three-dimensional simulation to determine simulated properties of the target area of the subterranean formation; and providing the simulated properties to a well planner for use in a hydrocarbon exploration or extraction process.

EXAMPLE #11

A method of the present disclosure can include receiving seismic data indicating locations of a plurality of geological bodies in a target area of a subterranean formation; providing the seismic data as input to a trained machine-learning model for determining whether the target area of the subterranean formation includes one or more types of geological bodies; in response to providing the seismic data as input to the trained machine-learning model, receiving an output from the trained machine-learning model indicating that the target area of the subterranean formation includes the one or more types of geological bodies; and executing one or more processing operations for facilitating hydrocarbon exploration or extraction based on the seismic data and the output from the trained machine-learning model. Some or all of the method steps can be implemented by a processor.

EXAMPLE #12

The method of Example #11 may involve the one or more types of geological bodies including a salt body, a water body, or a hydrocarbon body.

EXAMPLE #13

The method of any of Examples #11-12 may involve the one or more processing operations including: determining that a target type of geological body is present in the target area of the subterranean formation based on the output from the trained machine-learning model; executing an edge-detection algorithm on the seismic data to determine an outer boundary of the target type of geological body that is present in the target area of the subterranean formation; generating a graphical user interface that highlights the outer boundary relative to the seismic data; and displaying the graphical user interface on a display device.

EXAMPLE #14

The method of Example #13 may involve the graphical user interface including an outline of the outer boundary overtop of the seismic data to highlight the outer boundary; or the graphical user interface excluding seismic content external to the outer boundary from the seismic data to highlight the outer boundary.

EXAMPLE #15

The method of any of Examples #11-14 may involve the one or more processing operations including smoothing the seismic data by applying a median filter to the seismic data.

EXAMPLE #16

The method of any of Examples #11-15 may involve generating a seismic-attribute dataset based on the seismic data. The seismic-attribute dataset can include a plurality of data point values for a particular type of seismic attribute. Each data point value in the plurality of data point values can be generated by applying one or more algorithms to a corresponding data point in the seismic data. The method may also involve providing the seismic-attribute dataset as input to the trained machine-learning model in addition to the seismic data. The seismic-attribute dataset can be used by the trained machine-learning model in conjunction with the seismic data for determining whether the target area of the subterranean formation includes the one or more types of geological bodies.

EXAMPLE #17

The method of Example #16 may involve the particular type of seismic attribute being a relative acoustic impedance, an apparent polarity, a reflection strength, a root mean squared frequency, or an arc length.

EXAMPLE #18

The method of any of Examples #11-17 may involve, prior to receiving the seismic data: receiving training data that includes a plurality of seismic datasets, where the training data can indicate which of the one or more types of geological bodies are present in each seismic dataset among the plurality of seismic datasets, and where the training data can exclude the seismic data; and training a machine-learning model using the training data to generate the trained machine-learning model.

EXAMPLE #19

The method of any of Examples #11-18 may involve the one or more processing operations including: determining that the target area of the subterranean formation is suitable or unsuitable for drilling a wellbore by applying the output from the trained machine-learning model to a predefined set of rules; generating a graphical user interface indicating that the target area is suitable or unsuitable for drilling the wellbore, respectively; and displaying the graphical user interface on a display device.

EXAMPLE #20

A non-transitory computer-readable medium of the present disclosure can include program code that is executable by a processor for causing the processor to: receive seismic data indicating locations of a plurality of geological bodies in a target area of a subterranean formation; provide the seismic data as input to a trained machine-learning model for determining whether the target area of the subterranean formation includes one or more types of geological bodies; in response to providing the seismic data as input to the trained machine-learning model, receive an output from the trained machine-learning model indicating that the target

area of the subterranean formation includes the one or more types of geological bodies; and execute one or more processing operations for facilitating hydrocarbon exploration or extraction based on the seismic data and the output from the trained machine-learning model.

The foregoing description of certain examples, including illustrated examples, has been presented only for the purpose of illustration and description and is not intended to be exhaustive or to limit the disclosure to the precise forms disclosed. Numerous modifications, adaptations, and uses thereof will be apparent to those skilled in the art without departing from the scope of the disclosure. For instance, examples described herein can be combined together to yield still further examples.

The invention claimed is:

1. A system comprising:

a seismic source configured to generate seismic waves;

a seismic sensor configurable to detect the seismic waves output from the seismic source and generate seismic data based on the seismic waves;

a processor; and

a memory including instructions that are executable by the processor for causing the processor to:

receive the seismic data generated by the seismic sensor, the seismic data indicating locations of a plurality of geological bodies in a target area of a subterranean formation, wherein the target area of the subterranean formation excludes a wellbore and the seismic data is usable for assessing whether the target area of the subterranean formation is suitable for drilling the wellbore;

generate a seismic-attribute dataset based on the seismic data;

provide the seismic data and the seismic-attribute dataset as input to a trained machine-learning model, the trained machine-learning model including a dense layer to provide one or more identifiers indicating one or more types of geological bodies that are present in the target area of the subterranean formation, wherein a location of a target type of geological body in the subterranean formation affects whether the target area of the subterranean formation is suitable for drilling the wellbore, and wherein the target type of geological body includes a salt body or a hydrocarbon body;

in response to providing the seismic data as input to the trained machine-learning model, receive an output from the trained machine-learning model indicating that the target area of the subterranean formation includes the target type of geological body; and

execute one or more processing operations for facilitating hydrocarbon exploration or extraction based on the output from the trained machine-learning model, wherein the one or more processing operations include:

determining that the target type of geological body is present in the target area of the subterranean formation based on the output from the trained machine-learning model;

executing an edge-detection algorithm on the seismic data to determine an outer boundary of the target type of geological body that is present in the target area;

generating a graphical user interface that highlights the outer boundary relative to the seismic data to assist a well planner in determining the location of the target type of geological body in the target area; and

displaying the graphical user interface on a display device for assisting the well planner in determining whether the target area is suitable for drilling.

2. The system of claim **1**, wherein:

the graphical user interface includes an outline of the outer boundary overtop of the seismic data to highlight the outer boundary; or

the graphical user interface excludes seismic content external to the outer boundary from the seismic data to highlight the outer boundary.

3. The system of claim **1**, wherein the one or more processing operations include smoothing the seismic data by applying a median filter to the seismic data.

4. The system of claim **1**, wherein the seismic-attribute dataset includes a plurality of data point values for a particular type of seismic attribute, each data point value in the plurality of data point values being generated by applying one or more algorithms to a corresponding data point in the seismic data.

5. The system of claim **4**, wherein the particular type of seismic attribute is a relative acoustic impedance, an apparent polarity, a reflection strength, a root mean squared frequency, or an arc length.

6. The system of claim **1**, wherein the memory further includes instructions that are executable by the processor for causing the processor to, prior to receiving the seismic data:

receive training data that includes a plurality of seismic datasets, wherein the training data indicates which target type of geological body is present in each seismic dataset among the plurality of seismic datasets, and wherein the training data excludes the seismic data; and

train a machine-learning model using the training data to generate the trained machine-learning model.

7. The system of claim **1**, wherein the one or more processing operations include:

determining that the target area of the subterranean formation is suitable or unsuitable for drilling the wellbore by applying the output from the trained machine-learning model to a predefined set of rules;

generating the graphical user interface to indicate that the target area is suitable or unsuitable for drilling the wellbore, respectively; and

displaying the graphical user interface on the display device.

8. The system of claim **1**, wherein the one or more processing operations include:

generating a three-dimensional simulation of the target area of the subterranean formation based on the seismic data and the output from the trained machine-learning model;

executing the three-dimensional simulation to determine simulated properties of the target area of the subterranean formation; and

providing the simulated properties to the well planner for use in a hydrocarbon exploration or extraction process.

9. A method comprising:

receiving, by a processor, seismic data indicating locations of a plurality of geological bodies in a target area of a subterranean formation, wherein the seismic data is generated by one or more seismic sensors configured to detect seismic waves associated with the subterranean formation that are outputted by a seismic source;

generating, by the processor, a seismic-attribute dataset based on the seismic data;

providing, by the processor, the seismic data and the seismic-attribute dataset as input to a trained machine-learning model, the trained machine-learning model including a dense layer to provide one or more identifiers indicating one or more types of geological bodies that are present in the target area of the subterranean formation, wherein a location of a target type of geological body in the subterranean formation affects whether the target area of the subterranean formation is suitable for drilling a wellbore, and wherein the target type of geological body includes a salt body or a hydrocarbon body;

in response to providing the seismic data as input to the trained machine-learning model, receiving, by the processor, an output from the trained machine-learning model indicating that the target area of the subterranean formation includes the target type of geological body; and

executing, by the processor, one or more processing operations for facilitating hydrocarbon exploration or extraction based on the output from the trained machine-learning model, wherein the one or more processing operations include:

determining that the target type of geological body is present in the target area of the subterranean formation based on the output from the trained machine-learning model;

executing an edge-detection algorithm on the seismic data to determine an outer boundary of the target type of geological body that is present in the target area of the subterranean formation;

generating a graphical user interface that highlights the outer boundary relative to the seismic data to assist a well planner in determining a location of the target type of geological body in the target area; and

displaying the graphical user interface on a display device for assisting the well planner in determining whether the target area is suitable for drilling.

10. The method of claim **9**, wherein:

the graphical user interface includes an outline of the outer boundary overtop of the seismic data to highlight the outer boundary; or

the graphical user interface excludes seismic content external to the outer boundary from the seismic data to highlight the outer boundary.

11. The method of claim **9**, wherein the one or more processing operations include smoothing the seismic data by applying a median filter to the seismic data.

12. The method of claim **9**, wherein the seismic-attribute dataset includes a plurality of data point values for a particular type of seismic attribute, each data point value in the plurality of data point values being generated by applying one or more algorithms to a corresponding data point in the seismic data.

13. The method of claim **12**, wherein the particular type of seismic attribute is a relative acoustic impedance, an apparent polarity, a reflection strength, a root mean squared frequency, or an arc length.

14. The method of claim **9**, further comprising, prior to receiving the seismic data:

receiving training data that includes a plurality of seismic datasets, wherein the training data indicates which of the target type of geological body is present in each seismic dataset among the plurality of seismic datasets, and wherein the training data excludes the seismic data; and

training a machine-learning model using the training data to generate the trained machine-learning model.

15. The method of claim **9**, wherein the one or more processing operations include:

determining that the target area of the subterranean formation is suitable or unsuitable for drilling a wellbore by applying the output from the trained machine-learning model to a predefined set of rules; and

generating the display device.

16. A non-transitory computer-readable medium comprising program code that is executable by a processor for causing the processor to:

receive seismic data indicating locations of a plurality of geological bodies in a target area of a subterranean formation, the seismic data being generated by one or more seismic sensors configured to detect seismic waves associated with the subterranean formation output by a seismic source;

generate a seismic-attribute dataset based on the seismic data;

provide the seismic data and the seismic-attribute dataset as input to a trained machine-learning model, the trained machine-learning model including a dense layer to provide one or more identifiers indicating one or more types of geological bodies that are present in the target area of the subterranean formation, wherein a location of a target type of geological body in the subterranean formation affects whether the target area of the subterranean formation is suitable for drilling a wellbore, and wherein the target type of geological body includes a salt body or a hydrocarbon body;

in response to providing the seismic data as input to the trained machine-learning model, receive an output from the trained machine-learning model indicating that the target area of the subterranean formation includes the target type of geological body; and

execute one or more processing operations for facilitating hydrocarbon exploration or extraction based on the seismic data and the output from the trained machine-learning model, wherein the one or more processing operations include:

determining that the target type of geological body is present in the target area of the subterranean formation based on the output from the trained machine-learning model;

executing an edge-detection algorithm on the seismic data to determine an outer boundary of the target type of geological body that is present in the target area of the subterranean formation;

generating a graphical user interface that highlights the outer boundary relative to the seismic data to assist a well planner in determining a location of the target type of geological body in the target area; and

displaying the graphical user interface on a display device for assisting the well planner in determining whether the target area is suitable for drilling.

17. The non-transitory computer-readable medium of claim **16**, wherein:

the graphical user interface includes an outline of the outer boundary overtop of the seismic data to highlight the outer boundary; or

the graphical user interface excludes seismic content external to the outer boundary from the seismic data to highlight the outer boundary.

18. The non-transitory computer-readable medium of claim 16, wherein the one or more processing operations include smoothing the seismic data by applying a median filter to the seismic data.

19. The non-transitory computer-readable medium of claim 16, wherein the seismic-attribute dataset includes a plurality of data point values for a particular type of seismic attribute, each data point value in the plurality of data point values being generated by applying one or more algorithms to a corresponding data point in the seismic data.

20. The non-transitory computer-readable medium of claim 19, wherein the particular type of seismic attribute is a relative acoustic impedance, an apparent polarity, a reflection strength, a root mean squared frequency, or an arc length.

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