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Raghupathi

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(54) **GENERATING NOTIFICATIONS THROUGH CHART PATTERN DETECTION**

(71) Applicant: **SAP SE**, Walldorf (DE)

(72) Inventor: **Krishnan Raghupathi**, Bangalore (IN)

(73) Assignee: **SAP SE**, Walldorf (DE)

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CPC ***G06F 18/2415*** (2023.01); ***G06F 16/55*** (2019.01)

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None
See application file for complete search history.

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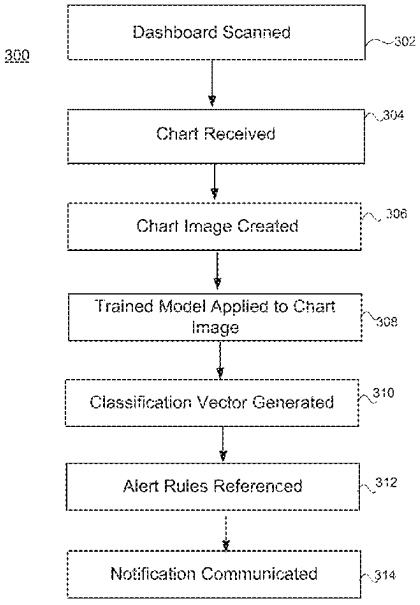
Primary Examiner — Augustine K. Obisesan
(74) *Attorney, Agent, or Firm* — Fountainhead Law Group, PC

(57) **ABSTRACT**

Embodiments utilize pattern recognition to generate notifications in connection with analytical applications. A dashboard of the analytical dashboard is scanned to intake charts of data therefrom. Images of the charts are created, and then matched with repository patterns of a trained deep transfer model (such as a Convolutional Neural Network model). Upon matching of a pattern by the model, an alert is generated and communicated to a user to indicate a trend in the analytical data. In this manner, embodiments automatically detect data trends based upon their visual appearance when plotted in a chart, rather than through resource-intensive analysis of individual data point values. In specific embodiments, the pattern recognition may be implemented by an in-memory database engine of an in-memory database responsible for storing charts and/or chart images and/or the repository. In some embodiments, recognition of patterns in chart images may be implemented by a service.

20 Claims, 9 Drawing Sheets



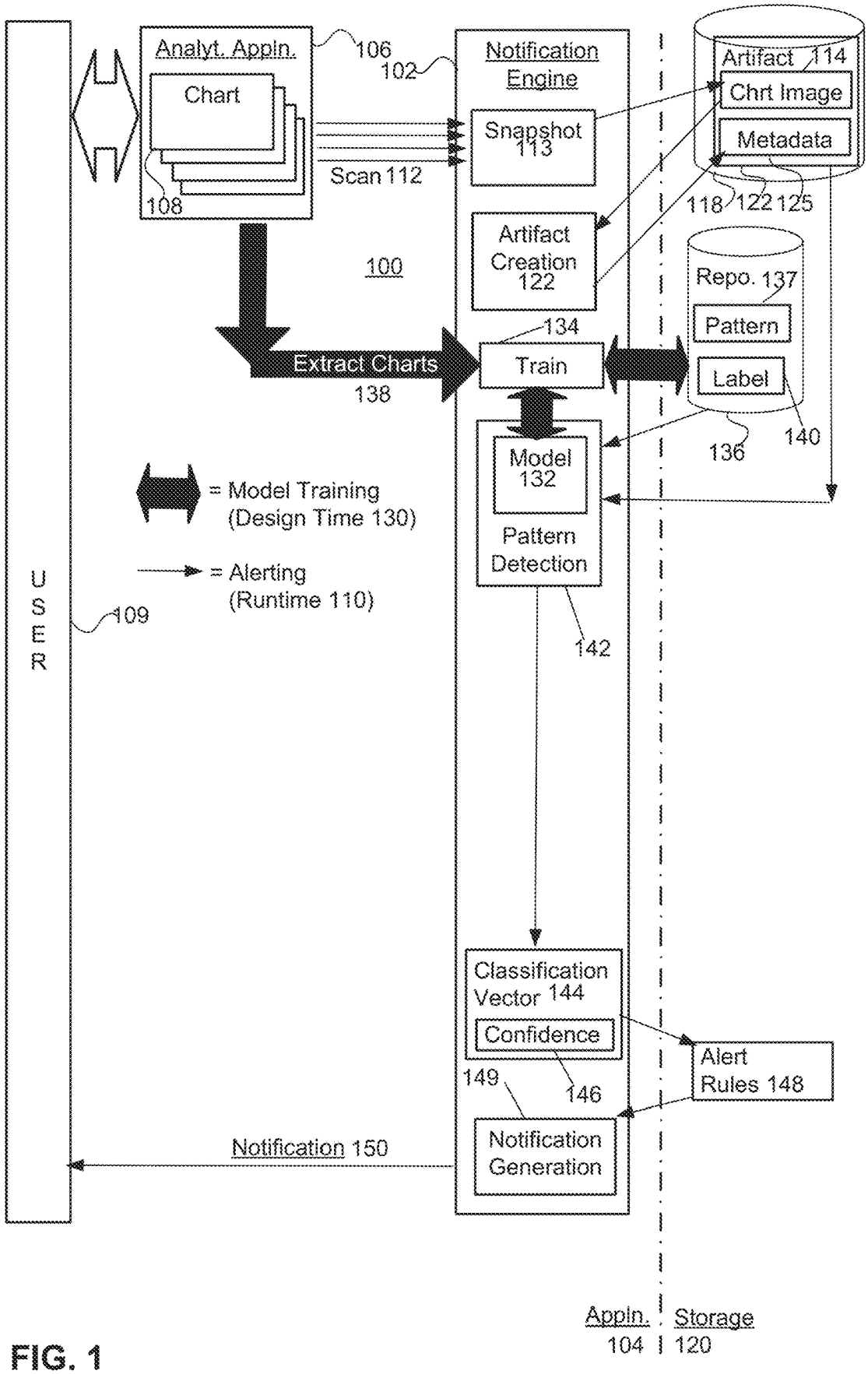

Analyt. Appln.
106
102
Chart
108
Scan 112
Notification Engine
Snapshot 113
Artifact 114
Chrt Image
Metadata
118
122
125
Artifact Creation 122
100
Repo. 137
Pattern
Label
134
Extract Charts 138
Train
136
140
Model 132
Pattern Detection
= Model Training (Design Time 130)
= Alerting (Runtime 110)
U S E R
109
142
Classification Vector 144
Confidence
Alert Rules 148
149
146
Notification Generation
Notification 150
Appln. 104
Storage 120

FIG. 1

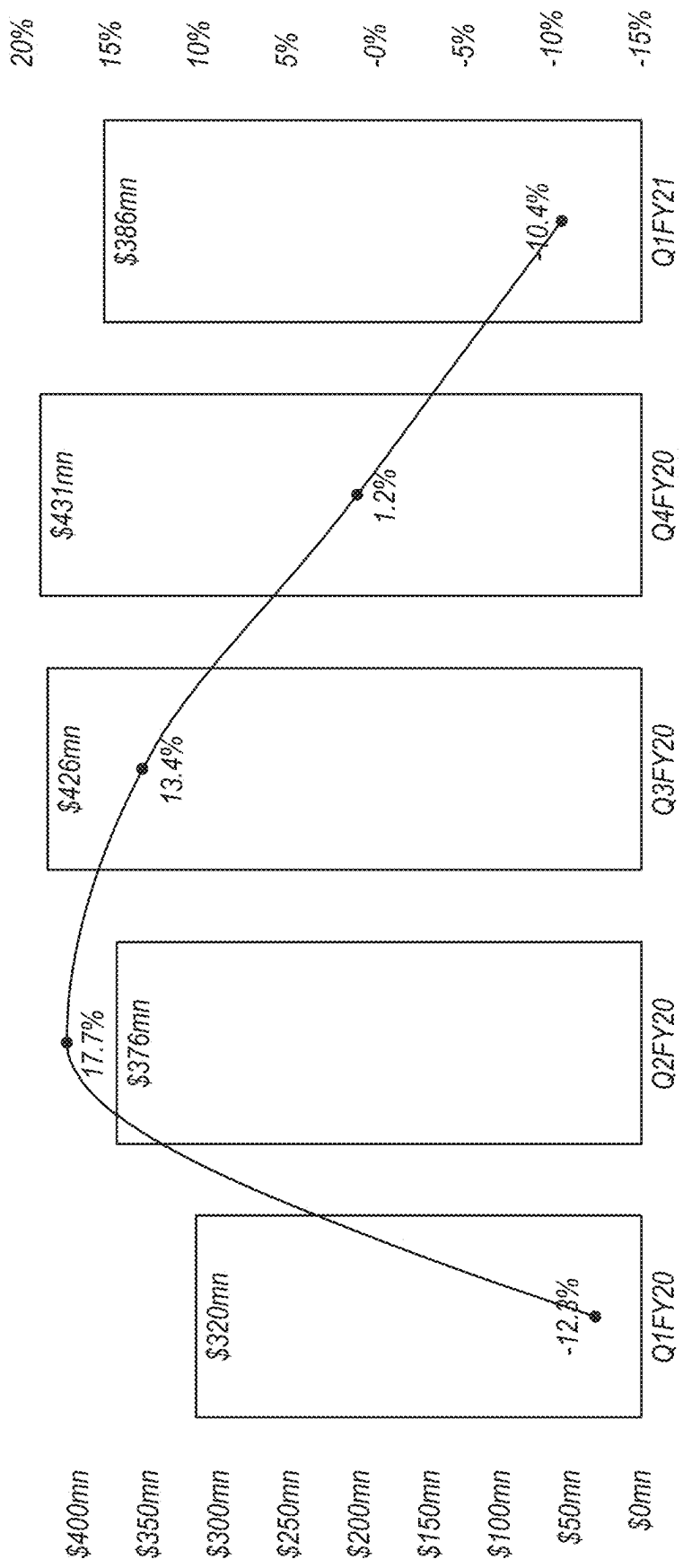

20%
15%
10%
5%
-0%
-5%
-10%
-15%
$386mn
$431mn
$426mn
$376mn
$320mn
10.4%
1.2%
13.4%
17.7%
-12.8%
Q1FY21
Q4FY20
Q3FY20
Q2FY20
Q1FY20
$400mn
$350mn
$300mn
$250mn
$200mn
$150mn
$100mn
$50mn
$0mn

FIG. 2

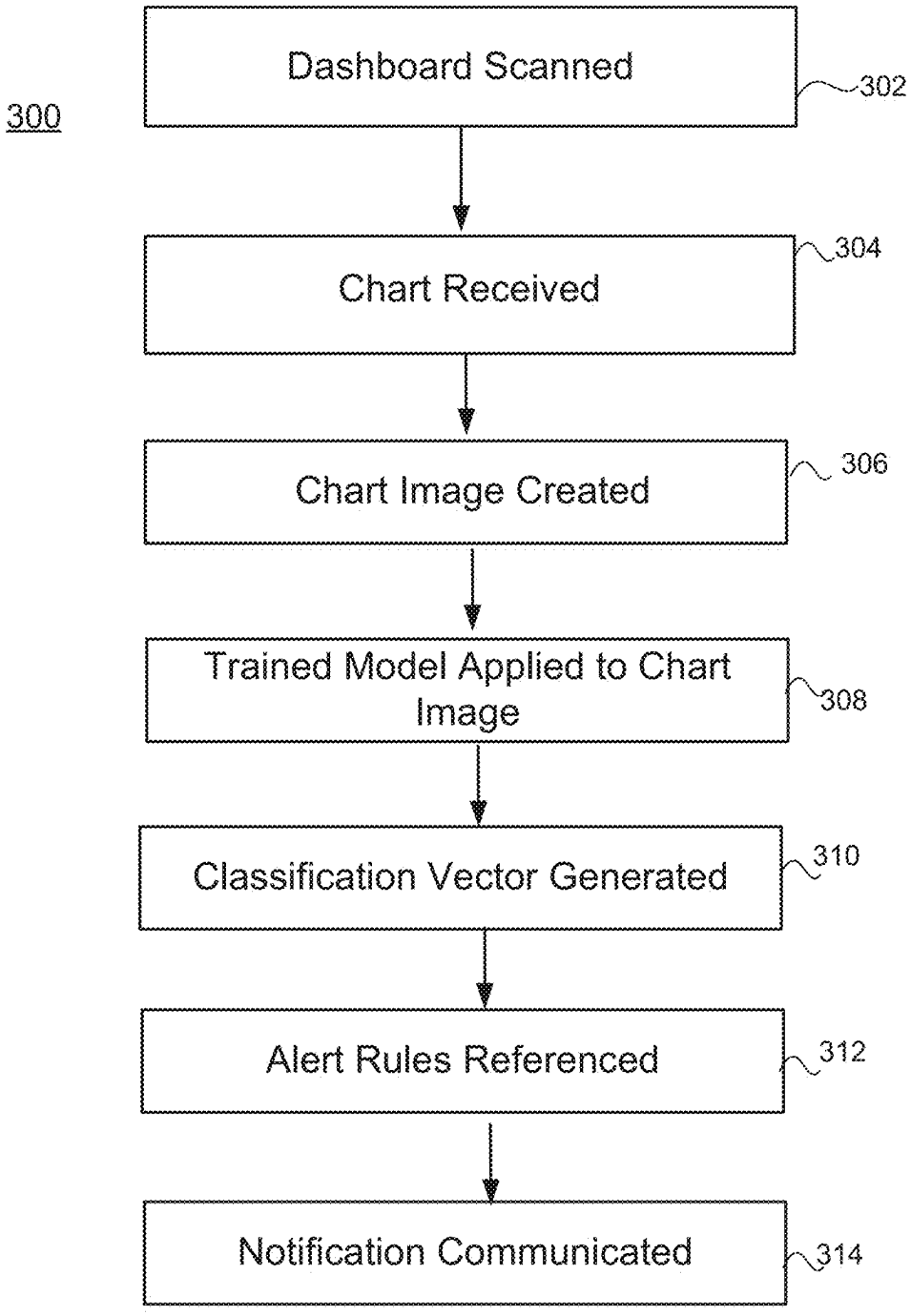

300
Dashboard Scanned
302
Chart Received
304
Chart Image Created
306
Trained Model Applied to Chart Image
308
Classification Vector Generated
310
Alert Rules Referenced
312
Notification Communicated
314

FIG. 3

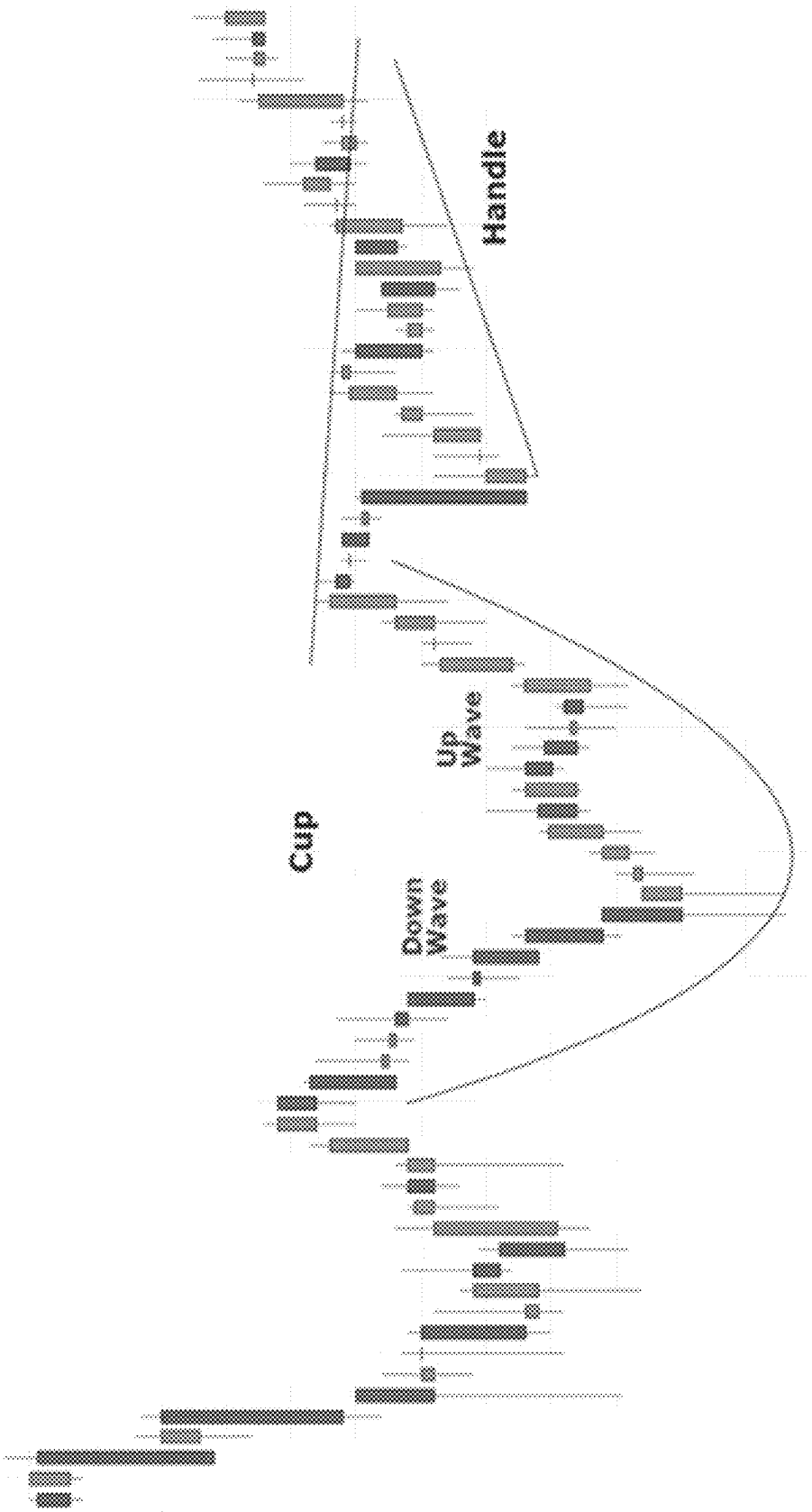


FIG. 4

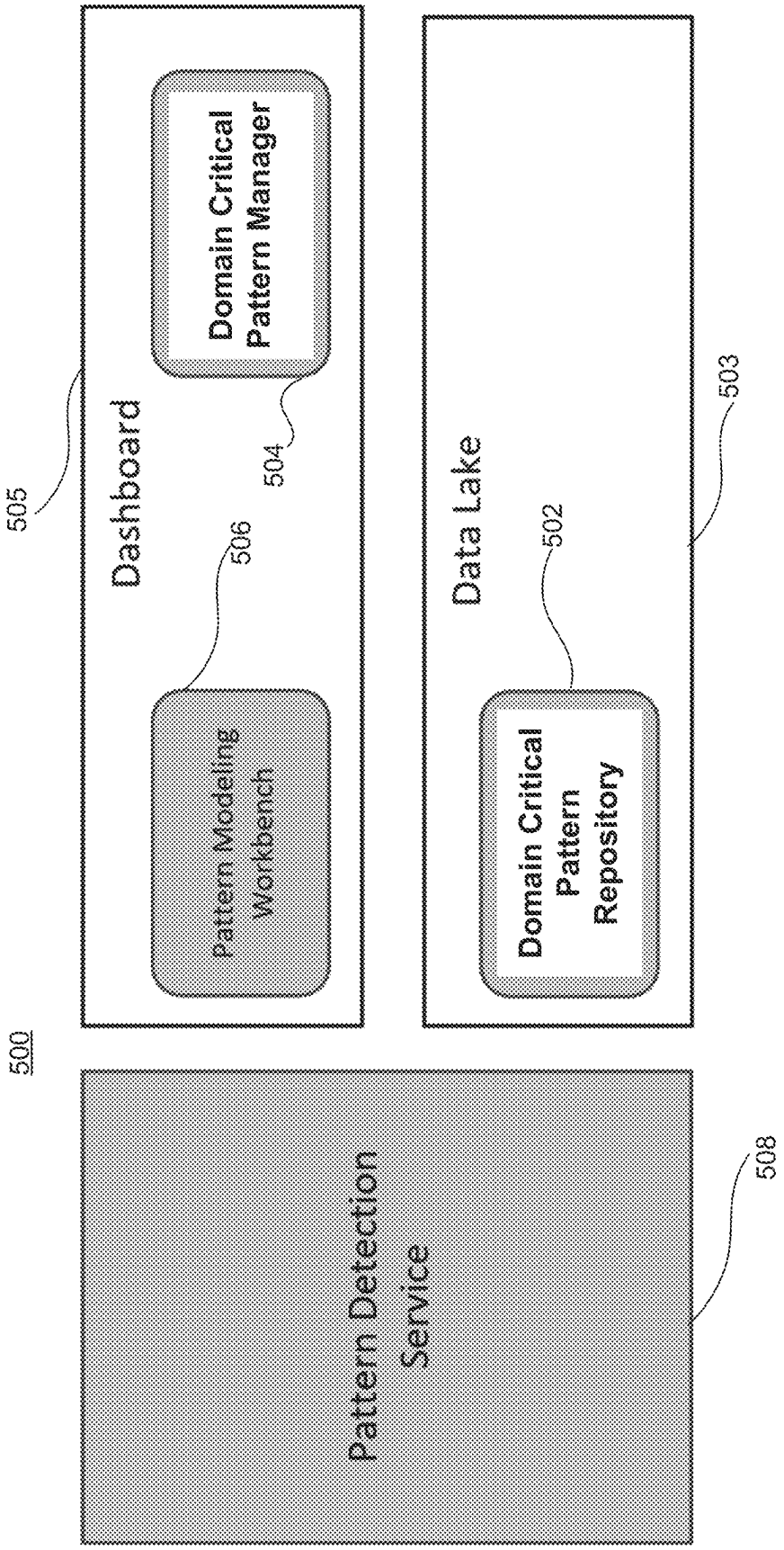

500
Dashboard
505
Domain Critical Pattern Manager
504
Pattern Modeling Workbench
506
Data Lake
503
Domain Critical Pattern Repository
502
Pattern Detection Service
508

FIG. 5

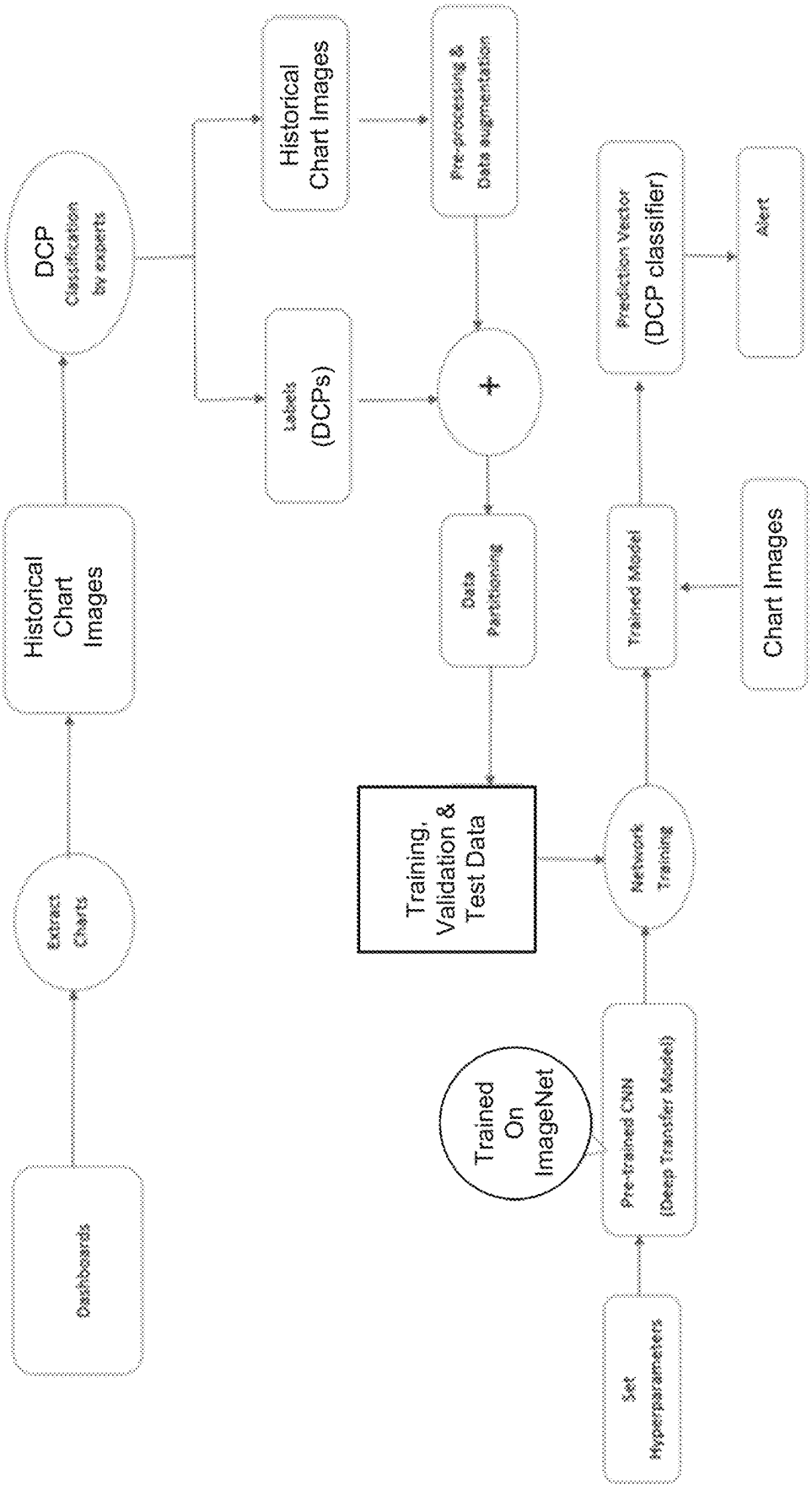

Dashboards
Extract Charts
Historical Chart Images
DCP Classification by experts
Historical Chart Images
Labels (DCPs)
Pre-processing & Data augmentation
+
Data Partitioning
Training, Validation & Test Data
Trained On ImageNet
Pre-trained CNN (Deep Transfer Model)
Set Hyperparameters
Network Training
Trained Model
Chart Images
Prediction Vector (DCP classifier)
Alert

FIG. 6

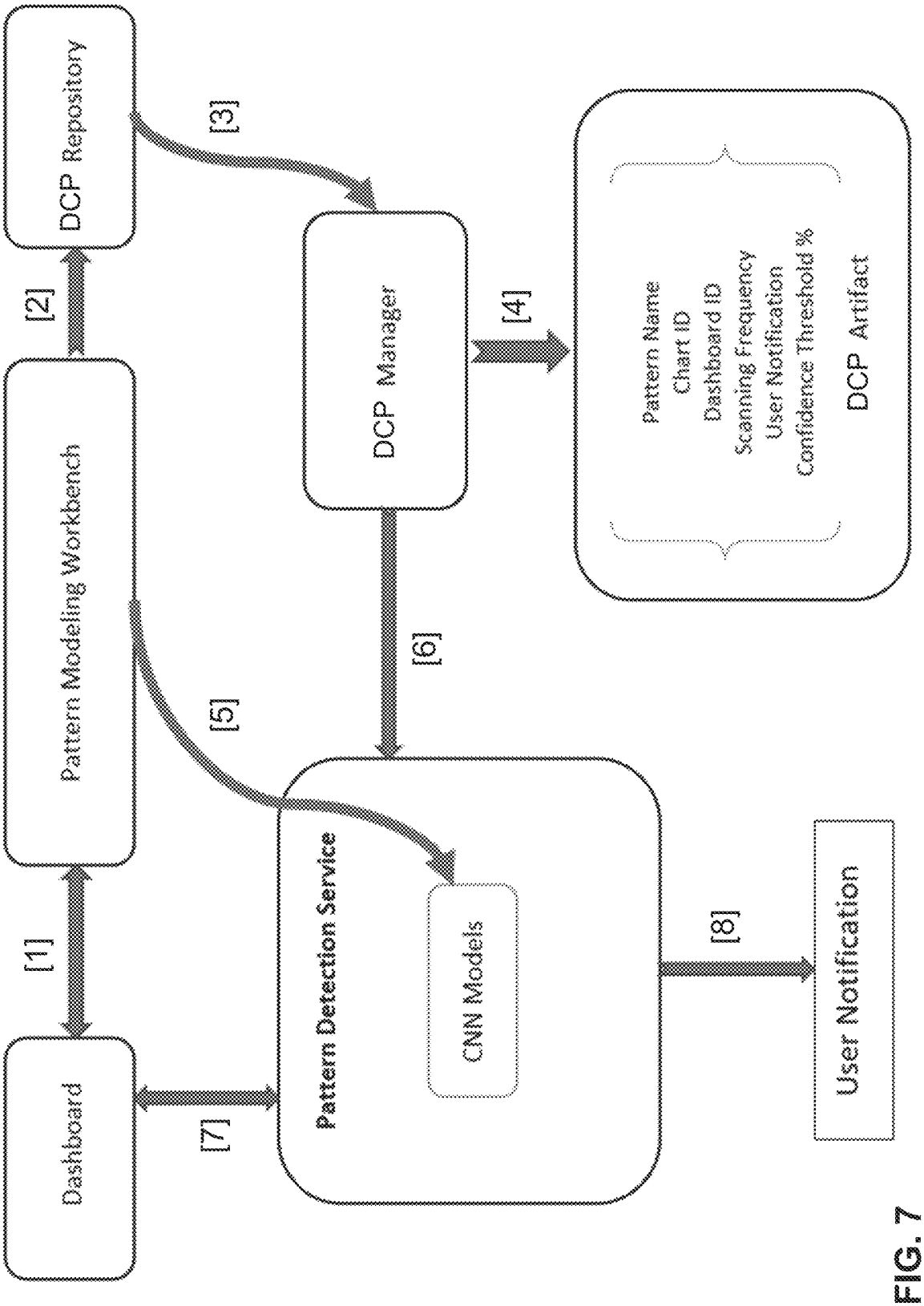

DCP Repository
[3]
[2]
DCP Manager
[4]
Pattern Name
Chart ID
Dashboard ID
Scanning Frequency
User Notification
Confidence Threshold %
DCP Artifact
Pattern Modeling Workbench
[6]
[5]
[1]
Pattern Detection Service
CNN Models
[8]
User Notification
Dashboard
[7]

FIG. 7

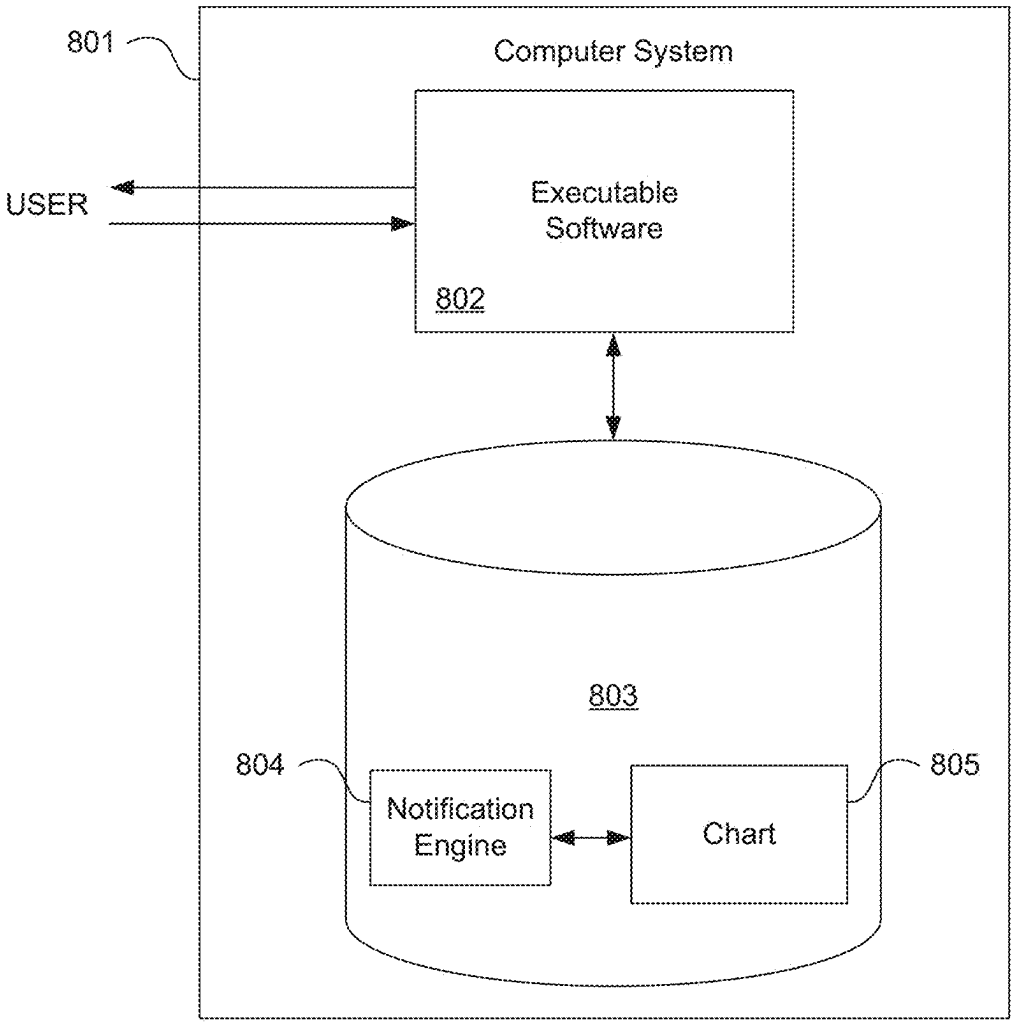

801
Computer System
USER
Executable Software
802
803
804
Notification Engine
Chart
805

FIG. 8

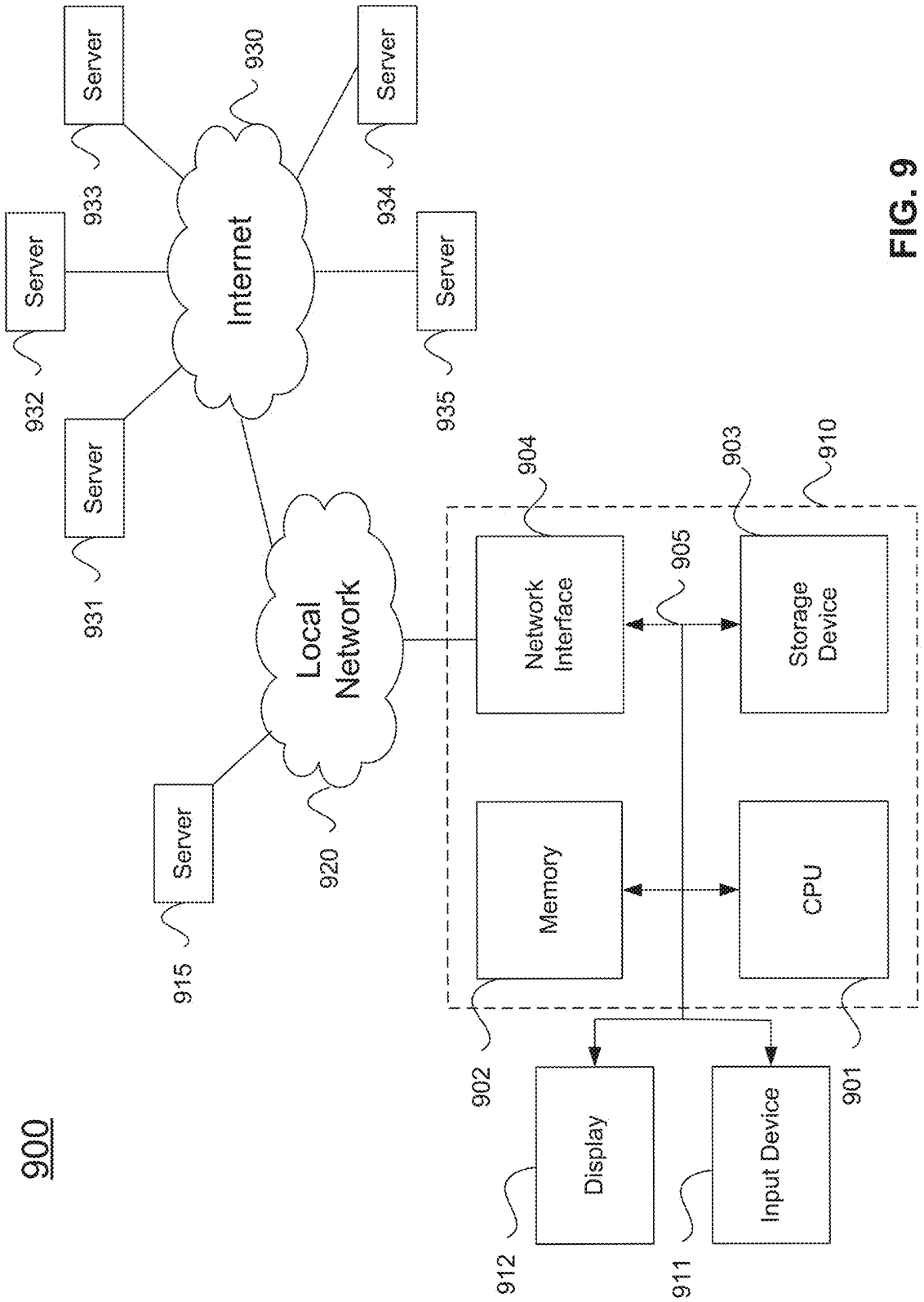

900
Internet
930
Server
933
Server
934
Server
932
Server
935
Server
931
Local Network
920
Server
915
Network Interface
904
Storage Device
903
910
905
Memory
902
CPU
901
Display
912
Input Device
911

FIG. 9

GENERATING NOTIFICATIONS THROUGH CHART PATTERN DETECTION

BACKGROUND

Unless otherwise indicated herein, the approaches described in this section are not prior art to the claims in this application and are not admitted to be prior art by inclusion in this section.

Analysts may depend upon data presented in dashboard views, in order to perform decision-making for in variety of different knowledge domains. Examples can include but are not limited to health care and financial forecasting.

However, an analyst's ability to rapidly make accurate decisions, can be affected by the sheer volume of data being presented in the dashboard. In particular, the increasing prevalence of big data flows can render effective analysis more difficult and time-consuming.

SUMMARY

Embodiments utilize pattern recognition to generate notifications in connection with analytical applications. A dashboard of the analytical application is scanned to intake charts of data therefrom. Images of the charts are created, and then matched with repository patterns by a trained deep transfer model (such as a Convolutional Neural Network model). Upon matching of a pattern by the model, an alert is generated and communicated to a user to indicate a trend in the analytical data. In this manner, embodiments automatically detect data trends based upon their visual appearance when plotted in a chart, rather than through resource-intensive analysis of individual data point values. In specific embodiments, the pattern recognition may be implemented by an in-memory database engine of an in-memory database responsible for storing charts and/or chart images and/or the repository. In some embodiments, recognition of patterns in chart images may be implemented by a service.

The following detailed description and accompanying drawings provide a better understanding of the nature and advantages of various embodiments.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** shows a simplified diagram of a system according to an embodiment.

FIG. **2** shows a simplified chart according to an embodiment.

FIG. **3** shows a simplified flow diagram of a method according to an embodiment.

FIG. **4** shows a simplified chart according to an example.

FIG. **5** shows an example of a system implementing notification generation according to the example.

FIG. **6** shows a simplified flow diagram according to the example.

FIG. **7** is a simplified diagram showing interaction of a pattern detection service with repository, manager, and workbench according to the example.

FIG. **8** illustrates hardware of a special purpose computing machine configured to implement notification generation according to an embodiment.

FIG. **9** illustrates an example computer system.

DETAILED DESCRIPTION

Described herein are methods and apparatuses that implement notification generation based upon pattern recognition in charts. In the following description, for purposes of explanation, numerous examples and specific details are set forth in order to provide a thorough understanding of embodiments according to the present invention. It will be evident, however, to one skilled in the art that embodiments as defined by the claims may include some or all of the features in these examples alone or in combination with other features described below, and may further include modifications and equivalents of the features and concepts described herein.

FIG. **1** shows a simplified view of an example system that is configured to implement alert generation according to an embodiment. Specifically, system **100** comprises a notification engine **102** located in application layer **104**.

Analytics application **106** is also present within the application layer. Analytics application includes multiple charts **108** which it has created in order to visualize data for a user **109**. Those charts may be present, e.g., within a dashboard of the analytics application.

During runtime **110**, the notification engine is configured to scan **112** the analytics application and intake charts therefrom (e.g., from the dashboard). Depending upon the particular embodiment, such scanning may take place on a scheduled basis, or may automatically take place upon the creation of a new chart or modification of an existing chart.

FIG. **2** shows one particular example of a chart that may be received from a dashboard according to a particular embodiment. This specific chart plots net income and sales revenue (Y-axes) per quarter (X-axis).

This data from the chart of FIG. **2** shows decreasing sales revenue after Q2FY20. The information in this chart may offer potentially actionable insights regarding Key Performance Indicators (KPIs) in a manner that is helpful to the user.

Moreover, the visual shape offered by the chart of FIG. **2** may be recognizable and allow for rapid assessment of a trend by the user. Accordingly, the notification engine takes a snapshot **113** of the incoming charts in order to create corresponding chart images **114**.

The image of the chart may be in one or more formats. Examples of such image formats can include but are not limited to:

- Joint Photographic Experts Group (JPEG or JPG)
- Portable Network Graphics (PNG)
- Graphics Interchange Format (GIF)
- Tagged Image File (TIFF)
- Photoshop Document (PSD)
- Portable Document Format (PDF)
- Encapsulated Postscript (EPS)
- Adobe Illustrator Document (AI)
- Adobe Indesign Document (INDD)
- Raw Image Formats (RAW).

The chart images are stored within database **118** of storage layer **120**. Moreover, the chart images are subject to further processing to create **122** artifacts **124** therefrom.

The artifacts that are stored in the database, include the chart image as well as metadata **125** associated therewith. A variety of different types of information can be stored in the metadata of the artifact. Examples of such information can include but are not limited to one or more of:

- identifier of a chart;
- chart axis names;
- identifier of a dashboard;
- frequency of scanning;

Moreover, the metadata of an artifact can be supplemented and updated with additional information relevant to alert generation. In particular, some of this metadata may

result from application of a deep transfer model to the chart image, to generate a match with a pattern known to be critical in a particular domain, and potentially indicative of valuable trend(s). Such metadata can include but is not limited to:

- name of a matched domain-critical pattern (e.g., revenue decline; cup-and-handle);
- user notification details;
- confidence threshold (e.g., in %).

In particular, during an earlier design time **130**, the notification engine has created a deep transfer model **132**. That deep transfer model is trained **134** based upon a repository **136** of patterns in **137** chart images that are known to indicate trends in data.

As part of the training, charts are extracted **138** from dashboard(s), and images are created therefrom. The training corpus includes labels **140** associated with the patterns by experts knowledgeable regarding the particular domain in question.

Returning now to runtime, the artifacts (including the images) are fed to the trained deep transfer model in order to perform pattern detection **142**. The result of processing of an artifact by the deep transfer model, is a classification vector **144**.

One dimension of a classification vector can comprise a confidence **146** (expressed, e.g., in a percentage) regarding the accuracy of the match by the model with a pattern present in the repository. As mentioned above, that confidence may be stored as metadata with the artifact.

Where appropriate, the classification vector can trigger the application of alert rules **148** to generate **149** a notification **150**. The alert rules can determine characteristics of a notification that is to be sent (by referencing, e.g., metadata of the artifact). Such notification characteristics can include but are not limited to one or more of

- notification recipient(s);
- notification urgency;
- notification repetition;
- notification format and content;
- channel of communication of notification (e.g., text, email, chat, other).

Notification generation that is performed according to various embodiments may offer one or more benefits. Specifically, one possible benefit is the rapid and accurate detection of domain-critical patterns arising in the dashboard of an analytics application, with reduced burden upon the user. That is, the user does not need to manually inspect the specific data present in every chart in order to recognize possibly actionable trends.

Another possible benefit is the ability to construct and maintain a repository of past-arising domain-specific patterns, that may be valuable for recognition and action. In this way, the user can be informed not just about historically important data, but also the visual patterns arising from such historically important data.

Still another possible benefit arises from the use of machine learning to recognize patterns arising in masses of data. In this manner, the limited resources of domain experts can be leveraged into effective recognition of important trends across large volumes of data.

FIG. **3** is a flow diagram of a method **300** according to an embodiment. At **302**, a dashboard is scanned.

At **304**, in response to the scanning, a chart is received. At **306**, an image of the chart is created.

At **308**, a trained model is applied to match the chart image with a pattern in a repository. At **310**, a classification vector is generated from the matching.

At **312**, alert rules are referenced to generate a notification from the classification vector. At **314**, the notification is communicated to a recipient.

Further details regarding alert generation according to various embodiments, are now provided in connection with the following example. In this particular example, alert generation is implemented in connection with the domain of stock purchasing, with trained Convolutional Neural Network (CNN) model(s) utilized as the deep transfer model.

EXAMPLE

FIG. **4** is a sample chart that plots the price (Y-axis) of a listed share over time (X-axis). In this chart, a cup-and-handle visual pattern is apparent.

Such a cup-and-handle visual pattern may be understood as a bullish signal extending an uptrend. For example, a trader may seek to recognize this pattern as an indicator, in order to place a stop buy order.

Accordingly, FIG. **5** shows a simplified architectural overview of a system that is configured to recognize a visual pattern in a chart and issue a corresponding alert. In particular, the system **500** comprises a domain-critical pattern repository **502** within a data lake **503**. This is a repository of chart screenshot images that are labelled and tagged with the identified domain critical pattern.

The system of FIG. **5** further includes a domain critical pattern manager **504** within dashboard **505**. This element supports the creation and management of domain-critical pattern artifacts.

The system of FIG. **5** also includes a pattern modeling workbench **506**. This is a Machine Learning-based workbench for the development, training and deployment of image recognition models. Those models can detect domain critical patterns from charts that are embedded within analytics dashboards.

The system of FIG. **5** further includes pattern detection service **508**. This element comprises a runtime engine that scans the analytics dashboard(s), and determines the presence of a pattern within charts residing in those dashboards.

Details regarding the domain critical pattern repository according to this example, are now provided. This embodiment utilizes trained image recognition models to look for patterns within the analytics dashboard(s).

The pattern repository may exhibit one or more support the following capabilities:

- allow subject matter experts to create and maintain labeled training data sets of chart images that identify a specific domain-critical pattern within the chart region;
- allow assignment and maintenance of pattern names to labelled training data sets.

Details regarding the domain critical pattern manager according to this example, are now provided. In this embodiment, a domain-critical pattern (DCP) within the analytical dashboard(s) can be searched for.

A domain-critical pattern (DCP) is an artifact that may one or more of the following:

- A. reference to a unique pattern name as defined in the business-critical pattern repository;
- B. references to the chart and dashboard to be scanned to detect occurrence of the pattern;
- C. frequency with which the pattern scanning should be carried out;
- D. user notification that should be generated whenever a pattern is found in the dashboard;

E. confidence percentage threshold to determine the accuracy of the pattern match.

The manager may support creation and maintenance of DCPs per the structure defined above.

Details regarding the pattern modeling workbench are now described. For this embodiment, accurate detection of user-defined domain critical patterns from chart images, involves a pattern modeling workbench with one or more of the following capabilities:

allow users to import training data sets for one or more business critical patterns from the business-critical pattern repository;

support the use of pre-trained CNN models (deep transfer models) to develop, train, and deploy models that can detect the DCPs within analytics dashboard(s).

FIG. **6** is a simplified workflow of elements that can be implicated in alert generation according to this particular example.

Details regarding the pattern detection service of the embodiment of FIG. **5** are now described. The pattern detection service is a runtime engine that scans the analytics dashboards for DCPs, and generates user notifications whenever the patterns are found.

The pattern detection service may perform these functions by interacting with the pattern repository, the pattern manager, and the pattern modeling workbench. The simplified schematic diagram of FIG. **7** provides a run-time view of this orchestration process.

Specifically, at [1] the pattern modeling workbench interacts with the analytical dashboards to extract snapshots of chart images. These snapshots form the basis of training data sets that are published to the DCP repository.

At [2] the pattern modeling workbench allows subject matter experts to annotate the domain-critical patterns in the chart regions, and then to subsequently publish the training data sets for pattern recognition to the DCP repository.

At [3] the DCP manager interacts with the DCP repository to support the creation and maintenance of DCP artifacts.

At [4] the DCP manager creates a DCP artifact having a specific defined structure.

At [5] the pattern modeling workbench generates trained CNN models, that are designed to detect the patterns as defined in a DCP artifact. These models are then deployed within the context of the pattern detection service.

At [6] the DCP manager registers the created DCP artifacts with the pattern detection service.

At [7] the pattern detection service monitors the analytical dashboard by taking screenshots of chart images. The pattern detection service prepares the extracted screenshots for pattern detection.

At [8] the pattern detection service uses the trained CNN models to detect the patterns corresponding to the defined DCP artifacts from the extracted screenshots. The pattern detection service in turn creates and issues the appropriate user notification based upon the defined confidence threshold percentage.

Using the system described in this example, trained CNN models may be developed and deployed to detect appearance of the cup and handle pattern in the trader's analytical dashboard. Based on the defined confidence threshold %, appropriate user notifications can be generated to allow the necessary action (e.g., issue stop hold order) to be taken.

Returning now to FIG. **1**, there the particular embodiment is depicted with the notification engine as being located outside of the database. However, this is not required.

Rather, alternative embodiments could leverage the processing power of an in-memory database engine (e.g., the in-memory database engine of the HANA in-memory database available from SAP SE), in order to perform one or more various functions as described above. For example, one or more of the following could be stored in an in-memory database, and be processed by an in-memory database engine:

chart(s);

image(s);

model(s);

repositor(ies).

Thus FIG. **8** illustrates hardware of a special purpose computing machine configured to perform notification generation according to an embodiment. In particular, computer system **801** comprises a processor **802** that is in electronic communication with a non-transitory computer-readable storage medium comprising a database **803**. This computer-readable storage medium has stored thereon code **805** corresponding to a notification engine. Code **804** corresponds to a chart or chart image. Code may be configured to reference data stored in a database of a non-transitory computer-readable storage medium, for example as may be present locally or in a remote database server. Software servers together may form a cluster or logical network of computer systems programmed with software programs that communicate with each other and work together in order to process requests.

In view of the above-described implementations of subject matter this application discloses the following list of examples, wherein one feature of an example in isolation or more than one feature of said example taken in combination and, optionally, in combination with one or more features of one or more further examples are further examples also falling within the disclosure of this application:

Example 1

Computer implemented systems and methods comprising:

scanning a dashboard of an analytics application;

receiving a chart in response to the scanning;

creating an image of the chart;

storing within a non-transitory computer readable storage medium, the chart image in an artifact comprising metadata;

applying a deep transfer model to match the chart image with a pattern present in a repository;

generating a classification vector from matching between the deep transfer model and the chart image;

referencing alert rules to generate a notification from the classification vector; and communicating the notification to a recipient.

Example 2

The computer implemented systems or methods of Example 1 further comprising training the deep transfer model by:

extracting historical charts from the analytics application;

taking images of the historical charts; and

associating domain-specific labels with the images of the historical charts,

wherein the classification vector is generated from the domain-specific labels and the metadata.

Example 3

The computer implemented systems or methods of any of Examples 1 or 2 wherein the deep transfer model comprises a Convolutional Neural Network (CNN) model.

Example 4

The computer implemented systems or methods of any of Examples 1, 2, or 3 wherein the classification vector comprises a confidence.

Example 5

The computer implemented systems or methods of any of Examples 1, 2, 3, or 4 wherein the metadata comprises a scanning frequency.

Example 6

The computer implemented systems or methods of any of Examples 1, 2, 3, 4, or 5 wherein the metadata identifies the dashboard.

Example 7

The computer implemented systems or methods of any of Examples 1, 2, 3, 4, 5, or 6 wherein the deep transfer model is applied to the chart image as a service.

Example 8

The computer implemented systems or methods of any of Examples 1, 2, 3, 4, 5, 6, or 7 wherein:

the non-transitory computer readable storage medium comprises an in-memory database; and

an in-memory database engine of the in-memory database applies the deep transfer model and generates the classification vector.

Example 9

The computer implemented systems or methods of Example 8 wherein:

the repository is also stored in the in-memory database; and

the in-memory database engine trains the deep transfer model from the repository.

An example computer system **900** is illustrated in FIG. **9**. Computer system **910** includes a bus **905** or other communication mechanism for communicating information, and a processor **901** coupled with bus **905** for processing information. Computer system **910** also includes a memory **902** coupled to bus **905** for storing information and instructions to be executed by processor **901**, including information and instructions for performing the techniques described above, for example. This memory may also be used for storing variables or other intermediate information during execution of instructions to be executed by processor **901**. Possible implementations of this memory may be, but are not limited to, random access memory (RAM), read only memory (ROM), or both. A storage device **903** is also provided for storing information and instructions. Common forms of storage devices include, for example, a hard drive, a magnetic disk, an optical disk, a CD-ROM, a DVD, a flash memory, a USB memory card, or any other medium from which a computer can read. Storage device **903** may include source code, binary code, or software files for performing the techniques above, for example. Storage device and memory are both examples of computer readable mediums.

Computer system **910** may be coupled via bus **905** to a display **912**, such as a Light Emitting Diode (LED) or liquid crystal display (LCD), for displaying information to a computer user. An input device **911** such as a keyboard and/or mouse is coupled to bus **905** for communicating information and command selections from the user to processor **901**. The combination of these components allows the user to communicate with the system. In some systems, bus **905** may be divided into multiple specialized buses.

Computer system **910** also includes a network interface **904** coupled with bus **905**. Network interface **904** may provide two-way data communication between computer system **910** and the local network **920**. The network interface **904** may be a digital subscriber line (DSL) or a modem to provide data communication connection over a telephone line, for example. Another example of the network interface is a local area network (LAN) card to provide a data communication connection to a compatible LAN. Wireless links are another example. In any such implementation, network interface **904** sends and receives electrical, electromagnetic, or optical signals that carry digital data streams representing various types of information.

Computer system **910** can send and receive information, including messages or other interface actions, through the network interface **904** across a local network **920**, an Intranet, or the Internet **930**. For a local network, computer system **910** may communicate with a plurality of other computer machines, such as server **915**. Accordingly, computer system **910** and server computer systems represented by server **915** may form a cloud computing network, which may be programmed with processes described herein. In the Internet example, software components or services may reside on multiple different computer systems **910** or servers **931-935** across the network. The processes described above may be implemented on one or more servers, for example. A server **931** may transmit actions or messages from one component, through Internet **930**, local network **920**, and network interface **904** to a component on computer system **910**. The software components and processes described above may be implemented on any computer system and send and/or receive information across a network, for example.

The above description illustrates various embodiments of the present invention along with examples of how aspects of the present invention may be implemented. The above examples and embodiments should not be deemed to be the only embodiments, and are presented to illustrate the flexibility and advantages of the present invention as defined by the following claims. Based on the above disclosure and the following claims, other arrangements, embodiments, implementations and equivalents will be evident to those skilled in the art and may be employed without departing from the spirit and scope of the invention as defined by the claims.

What is claimed is:

1. A method comprising:

storing a plurality of patterns in a repository, each pattern including metadata comprising a reference to a unique pattern name, a reference to a chart in a dashboard of an analytic application to be monitored, and a confidence threshold;

scanning the dashboard of the analytics application;

creating a chart image of a first chart;

applying a deep transfer model to match the chart image with a first pattern of the plurality of patterns present in the repository based on the metadata;

generating a classification vector from matching between the deep transfer model and the chart image;

referencing a first confidence threshold of the first pattern to generate a notification from the classification vector; and

communicating the notification to a recipient.

2. A method as in claim **1** further comprising training the deep transfer model by:

extracting historical charts from the analytics application;

taking images of the historical charts; and

associating domain-specific labels with the images of the historical charts,

wherein the classification vector is generated from the domain-specific labels and the metadata.

3. A method as in claim **2** wherein the plurality of patterns in the repository are generated from the images of the historical charts.

4. A method as in claim **1** wherein the classification vector comprises a confidence.

5. A method as in claim **1** wherein the metadata comprises a scanning frequency.

6. A method as in claim **1** wherein the metadata identifies the dashboard.

7. A method as in claim **1** wherein the deep transfer model is applied to the chart image as a service.

8. A method as in claim **1** wherein:

the non-transitory computer readable storage medium comprises an in-memory database; and

an in-memory database engine of the in-memory database applies the deep transfer model and generates the classification vector.

9. A method as in claim **8** wherein:

the repository is also stored in the in-memory database; and

the in-memory database engine trains the deep transfer model from the repository.

10. A non-transitory computer readable storage medium embodying a computer program for performing a method, said method comprising:

training a deep transfer model by:

extracting historical charts from an analytics application;

taking images of the historical charts; and

associating domain-specific labels with images of the historical charts;

storing a plurality of patterns in a repository, each pattern including metadata comprising a reference to a unique pattern name, a reference to a chart in a dashboard of an analytic application to be monitored, and a confidence threshold;

scanning the dashboard of the analytics application;

creating a chart image of a first chart;

applying a deep transfer model to match the chart image with a first pattern of the plurality of patterns present in the repository based on the metadata;

generating a classification vector from matching between the deep transfer model and the chart image;

referencing a first confidence threshold of the first pattern to generate a notification from the classification vector; and

communicating the notification to a recipient.

11. A non-transitory computer readable storage medium as in claim **10** wherein the classification vector comprises a confidence.

12. A non-transitory computer readable storage medium as in claim **10** wherein the deep transfer model comprises a Convolutional Neural Network.

13. A non-transitory computer readable storage medium as in claim **10** wherein the deep transfer model is applied as a service.

14. A non-transitory computer readable storage medium as in claim **10** wherein:

the non-transitory computer readable storage medium comprises an in-memory database; and

an in-memory database engine of the in-memory database applies the deep transfer model and generates the classification vector.

15. A non-transitory computer readable storage medium as in claim **14** wherein:

the repository is stored in the in-memory database; and

the in-memory database engine trains the deep transfer model.

16. A computer system comprising:

one or more processors;

a software program, executable on said computer system, the software program configured to cause an in-memory database engine of an in-memory database to:

store a plurality of patterns in a repository, each pattern including metadata comprising a reference to a unique pattern name, a reference to a chart in a dashboard of an analytic application to be monitored, and a confidence threshold;

scan the dashboard of the analytics application;

create a chart image of a first chart;

apply a deep transfer model to match the chart image with a first pattern of the plurality of patterns present in the repository based on the metadata;

generate a classification vector from matching between the deep transfer model and the chart image;

reference a first confidence threshold of the first pattern to generate a notification from the classification vector; and

communicate the notification to a recipient.

17. A computer system as in claim **16** wherein the in-memory database engine is further configured to train the deep transfer model by:

extracting historical charts from the analytics application;

taking images of the historical charts; and

associating domain-specific labels with the images of the historical charts,

wherein the classification vector is generated from the domain-specific labels and the metadata.

18. A computer system as in claim **16** wherein the repository is stored in the in-memory database.

19. A computer system as in claim **16** wherein the classification vector comprises a confidence.

20. A computer system as in claim **16** wherein the deep transfer model comprises a Convolutional Neural Network (CNN) stored in the in-memory database.

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