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(54) SYSTEM FOR IDENTIFYING HANDWRITTEN CHARACTERS ON AN IMAGE USING A CLASSIFICATION MODEL

(71) Applicant: **Truist Bank**, Charlotte, NC (US)

(72) Inventor: **Raphael Fitzgerald**, Winston-Salem, NC (US)

(73) Assignee: **TRUIST BANK**, Charlotte, NC (US)

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Related U.S. Application Data

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(51) **Int. Cl.**

G06V 30/226 (2022.01)
G06N 3/088 (2023.01)

(52) **U.S. Cl.**

CPC ***G06V 30/226*** (2022.01); ***G06N 3/088*** (2013.01)

(58) **Field of Classification Search**

CPC G06V 30/15; G06V 30/226; G06V 30/42; G06V 30/19173; G06V 30/19107; G06V 30/1452; G06V 10/82; G06N 3/088

See application file for complete search history.

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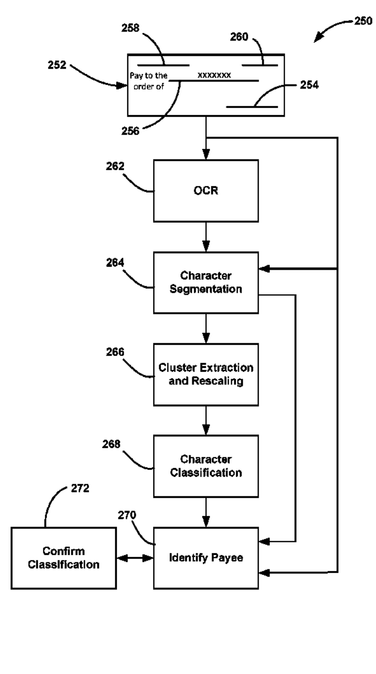
Primary Examiner — John R Wallace

(74) *Attorney, Agent, or Firm* — Michael A. Springs, Esq.; Shumaker, Loop & Kendrick, LLP; Patrick B. Horne

(57) **ABSTRACT**

A system for identifying handwritten characters on an image using a classification model that employs a neural network. The system includes a computer having a processor and a memory device that stores data and executable code that, when executed, causes the processor to read and convert typed text on the image to machine encoded text to identify locations of the typed text on the image; identify a location on the image that includes handwritten text based on the location of predetermined typed text on the image; identify clusters of non-white pixels in the image at the location having the handwritten text, where constraints are employed to refine and limit the clusters; generate an individual and separate cluster image for each identified cluster; and classify each cluster image using machine learning and at least one neural network to determine the likelihood that the cluster is a certain character.

20 Claims, 7 Drawing Sheets



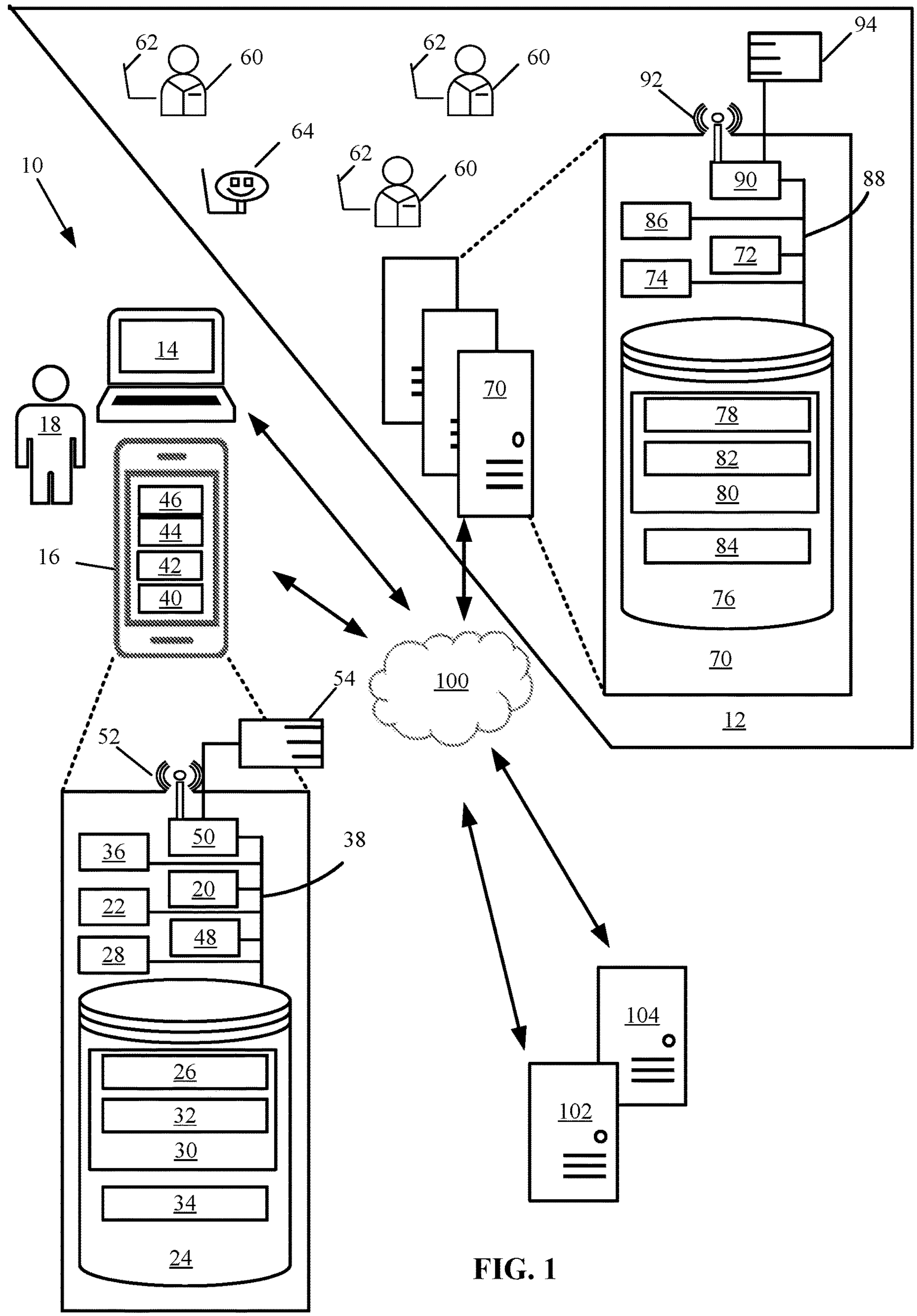

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FIG. 1

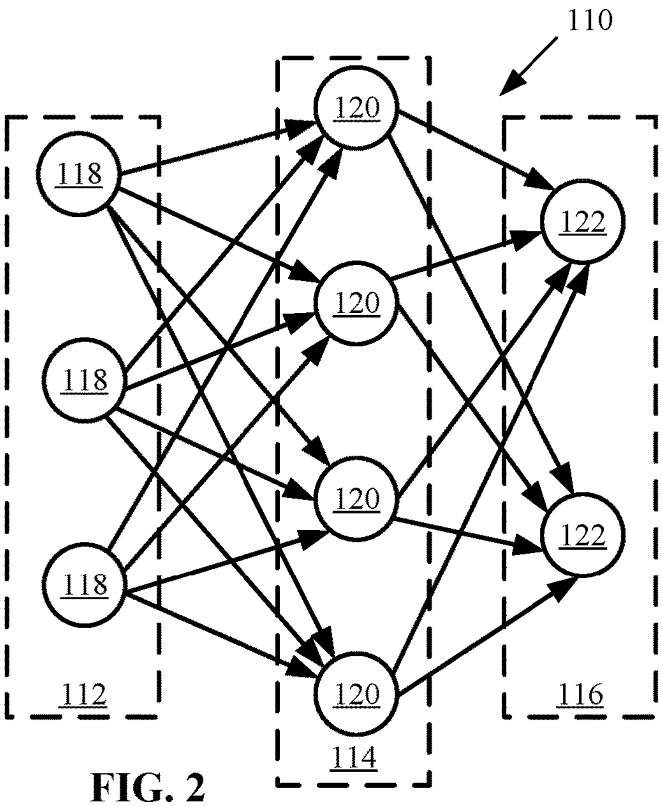


FIG. 2

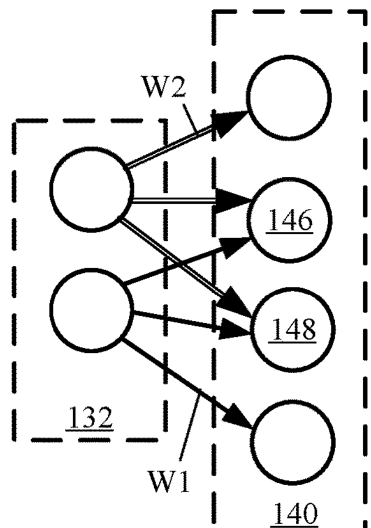
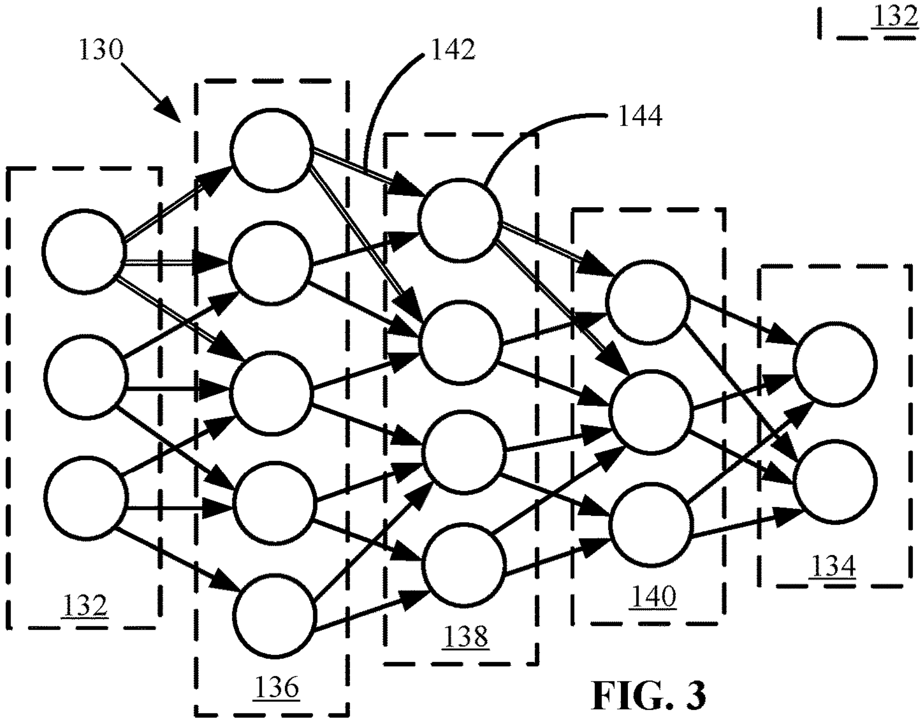


FIG. 4



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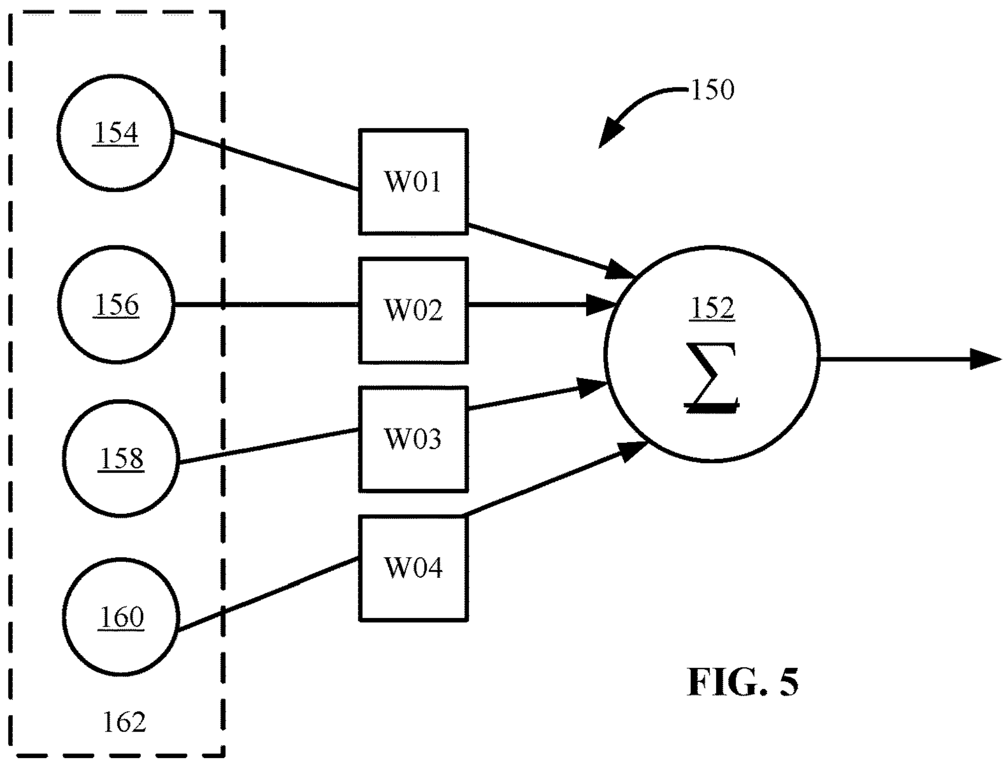
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FIG. 5

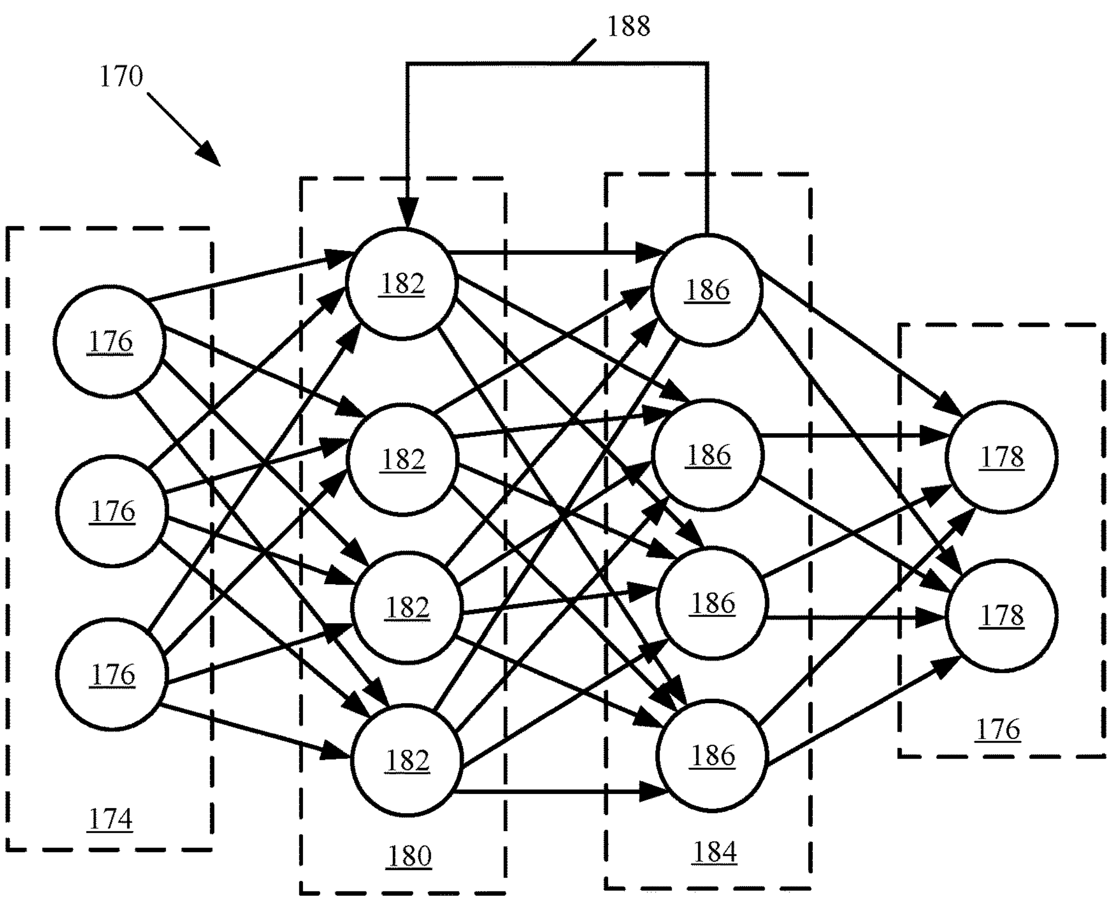
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FIG. 6

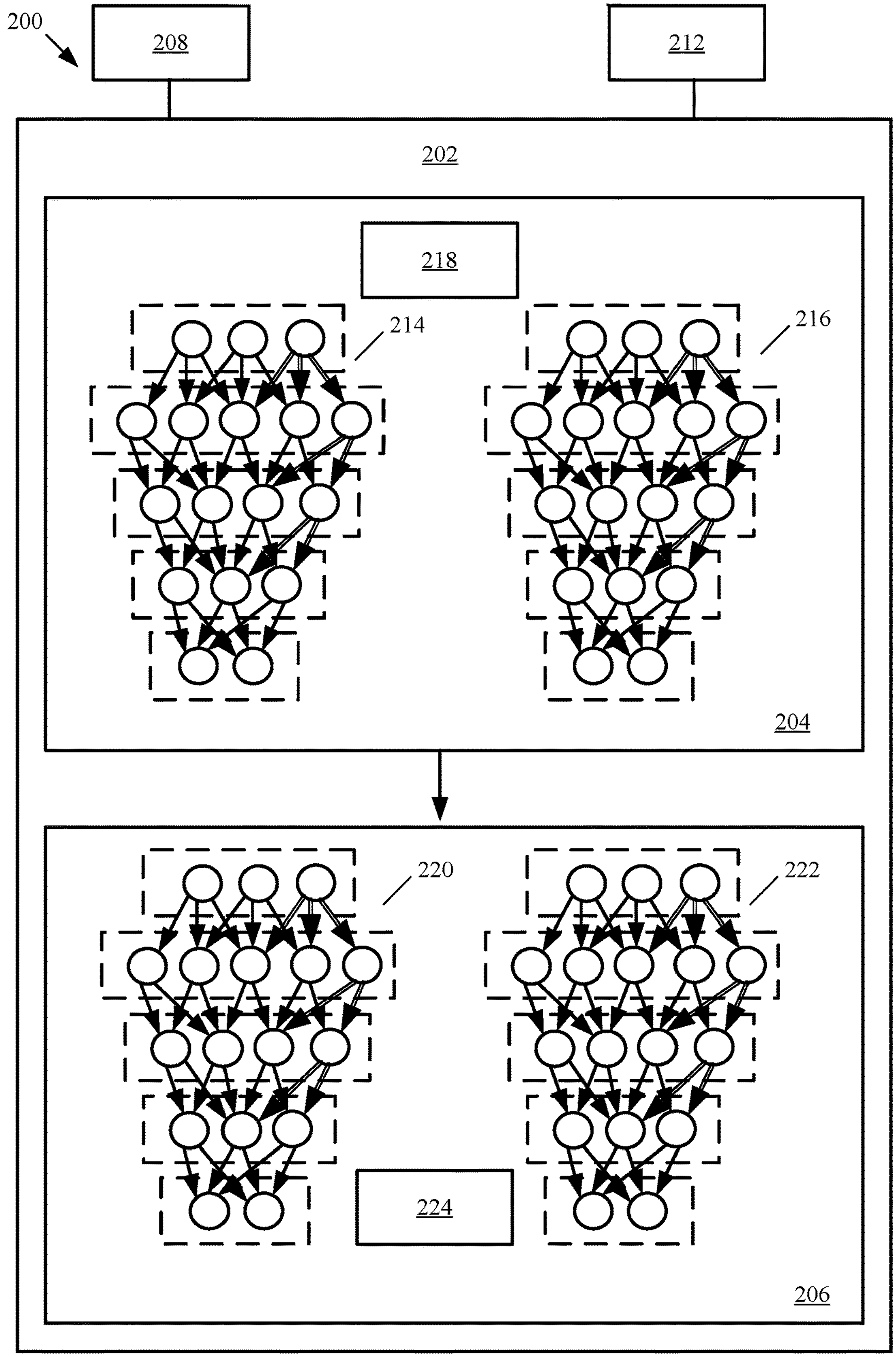
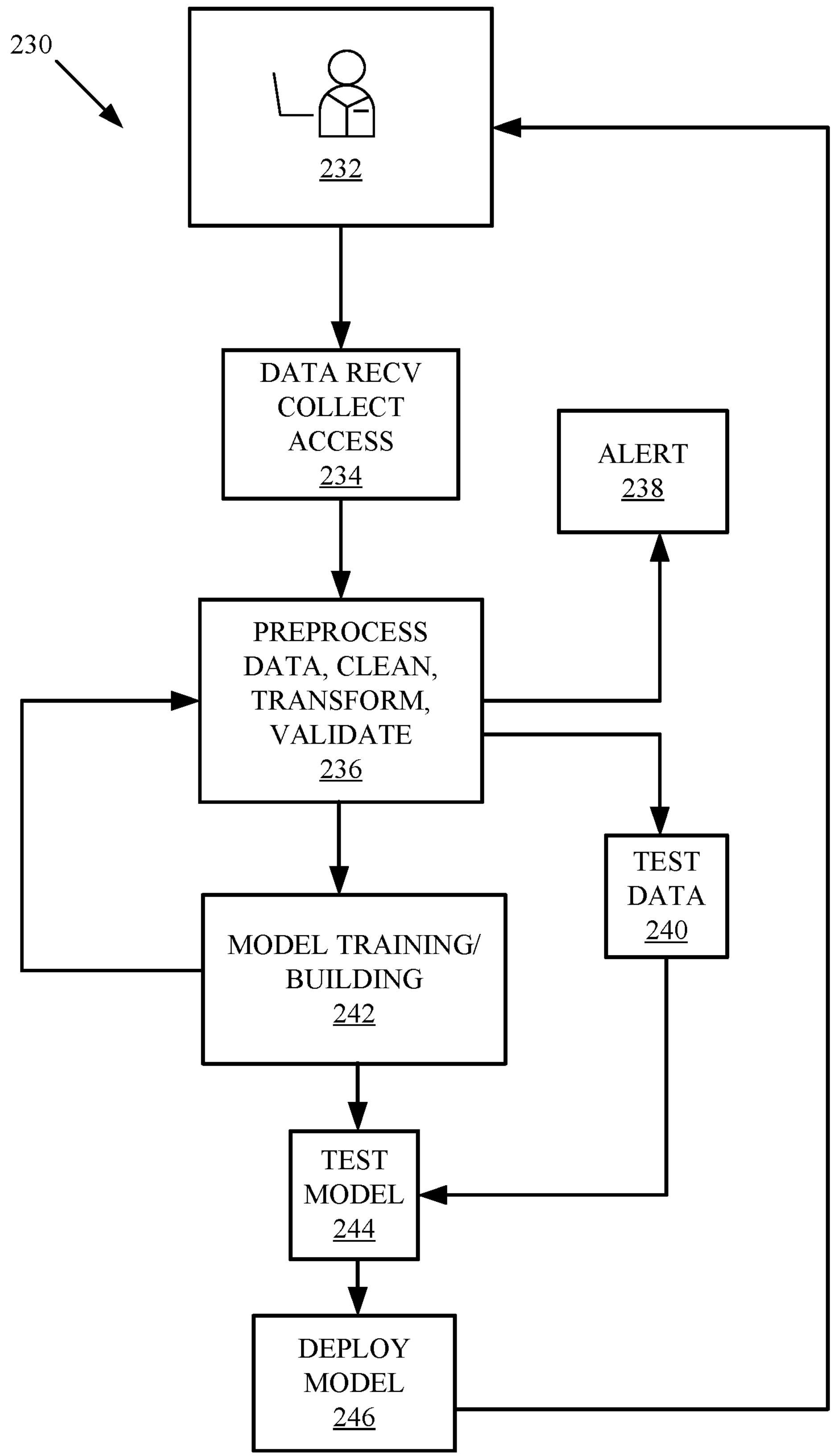


FIG. 7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MODEL
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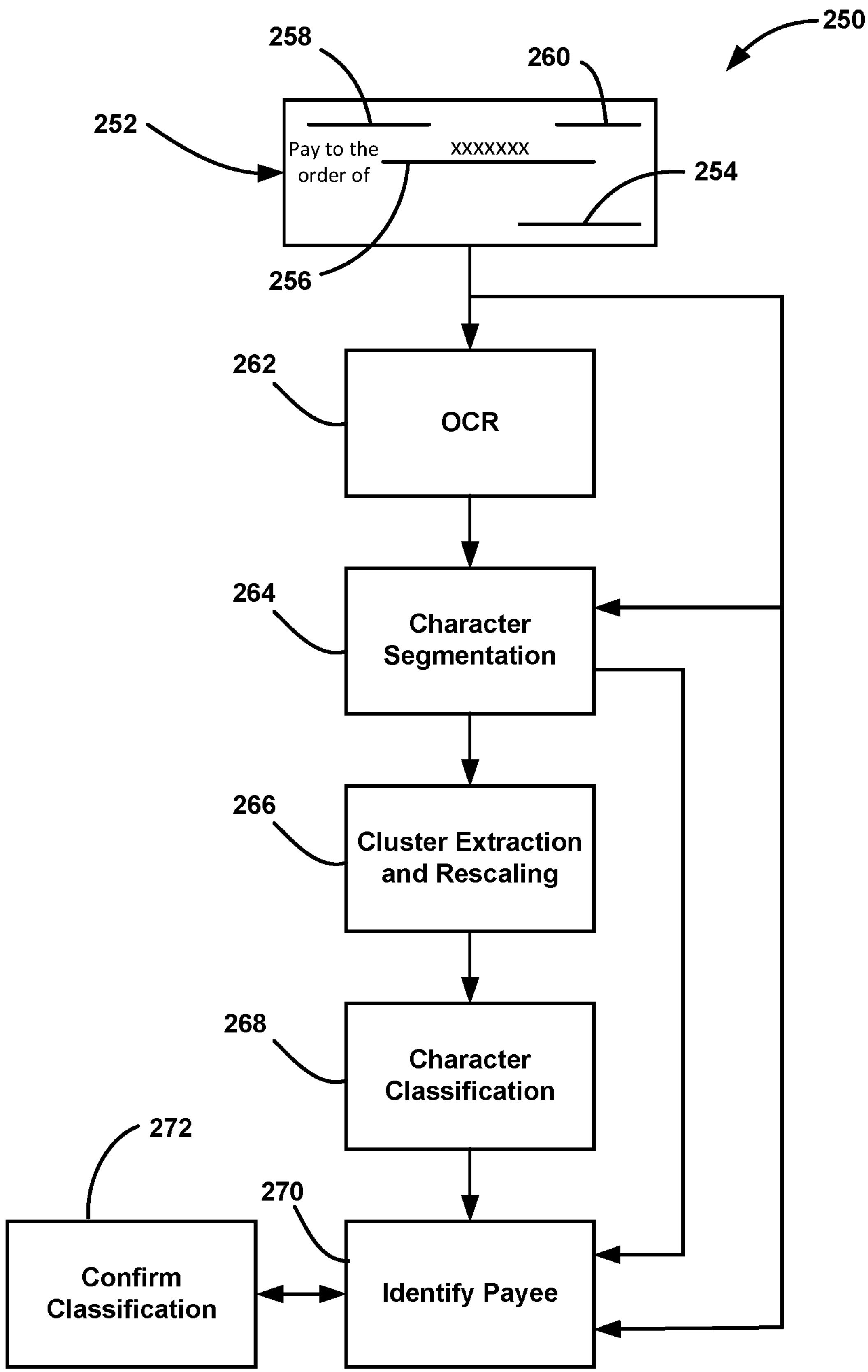
FIG. 8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Character Classification
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Confirm Classification
Identify Payee

FIG. 9

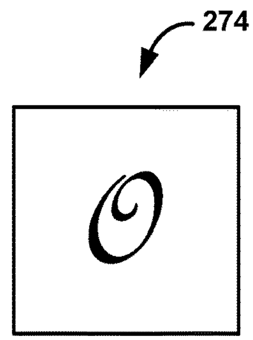

FIG. 10

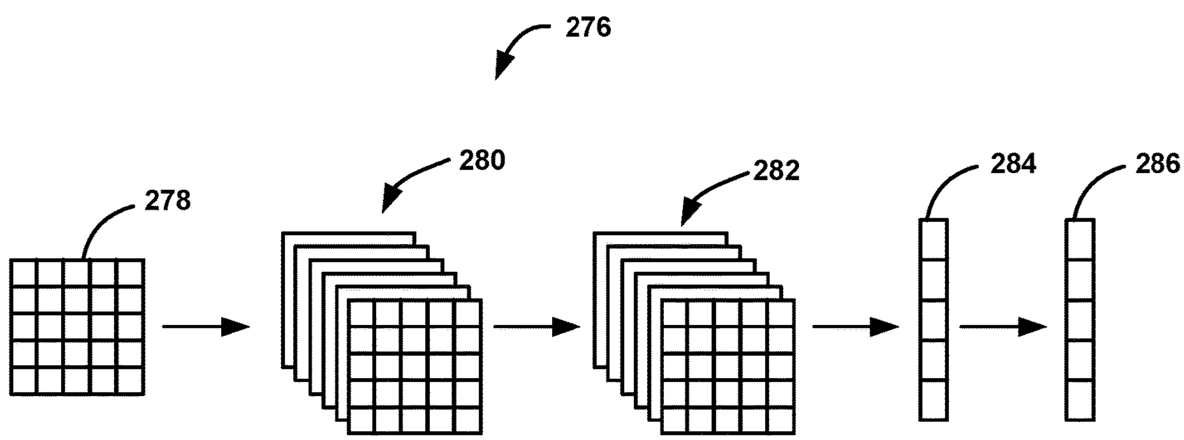

FIG. 11

SYSTEM FOR IDENTIFYING HANDWRITTEN CHARACTERS ON AN IMAGE USING A CLASSIFICATION MODEL

CROSS REFERENCE TO RELATED APPLICATIONS

This application is a continuation application tracing priority to co-pending U.S. application Ser. No. 17/661,654 filed on May 2, 2022, the entirety of which is herein expressly incorporated by reference.

BACKGROUND

Field

This disclosure relates generally to a system and method for identifying handwritten characters on an image and, more particularly, to a system and method for identifying handwritten characters on an image using a classification model that employs a neural network, where the system and method identify clusters of non-white pixels in the image at a location having handwritten text, and where each cluster is presumed to be a handwritten character, and where the processor employs constraints so that separate clusters are not identified in a stacked up/down direction relative to a writing direction of the handwritten text, that limits a size of each cluster to be less than a predetermined size and/or that requires all of the clusters to be within a certain percentage size of each other.

Discussion

A bank is a financial institution that is licensed to receive deposits from individuals and organizations and to make loans to those individuals and organizations or others. Banks may also perform other services such as wealth management, currency exchange, etc. Therefore, a bank may have thousands of customers and clients. Depending on the services that a bank provides, it may be classified as a retail bank, a commercial bank, an investment bank or some combination thereof. A retail bank typically provides services such as checking and savings accounts, loan and mortgage services, financing for automobiles, and short-term loans such as overdraft protection. A commercial bank typically provides credit services, cash management, commercial real estate services, employer services, trade finance, etc. An investment bank typically provides corporate clients with complex services and financial transactions such as underwriting and assisting with merger and acquisition activity.

Most people and businesses have a checking account that they write checks from to pay other people and businesses for goods and services. When those other people and businesses deposit the check into their account the check is generally scanned as an image and submitted to an automated clearing house (ACH) to process the transaction, which is a computer-based electronic network for processing transactions. Through this process the image of the check is returned to the bank from which it was drawn to be paid and is automatically connected to the account that it was drawn from. The transaction record and check image is accessible and displayed for the owner of the account online and through a mobile application on a transaction register. However, for handwritten checks the automated process that populates the transaction register generally only shows the transaction date, the check number and the amount because

the handwritten payee is not detectable by current automated processes. If the owner wants to see the payee of the check, he needs to click on the check image, which is a layer of inconvenience.

SUMMARY

The following discussion discloses and describes a system and method for identifying handwritten characters on an image using a classification model that employs a neural network. The system includes a computer having a processor and a memory device that stores data and executable code that, when executed, causes the processor to read and convert typed text on the image to machine encoded text to identify locations of the typed text on the image; identify a location on the image that includes handwritten text based on the location of predetermined typed text on the image; identify clusters of non-white pixels in the image at the location having the handwritten text, where each cluster is presumed to be a handwritten character, and where the processor employs constraints so that separate clusters are not identified in a stacked up/down direction relative to a writing direction of the handwritten text, that limits a size of each cluster to be less than a predetermined size and/or that requires all of the clusters to be within a certain percentage size of each other; generate an individual and separate cluster image for each identified cluster; classify each cluster image using machine learning and at least one neural network to determine the likelihood that the cluster is a certain character; and determine what character each cluster image is based on the classification.

Additional features of the disclosure will become apparent from the following description and appended claims, taken in conjunction with the accompanying drawings.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** illustrates a system and environment thereof by which a user benefits through use of services and products of an enterprise system;

FIG. **2** is a diagram of a feedforward network;

FIG. **3** is a diagram of a convolutional neural network (CNN);

FIG. **4** is a diagram of a portion of the CNN shown in FIG. **3** illustrating assigned weights at connections or neurons;

FIG. **5** is a diagram representing an exemplary weighted sum computation in a node in an artificial neural network;

FIG. **6** is a diagram of a recurrent neural network (RNN) utilized in machine learning;

FIG. **7** is a schematic logic diagram of an artificial intelligence processor operating an artificial intelligence program;

FIG. **8** is a flow chart showing a method for model development and deployment by machine learning;

FIG. **9** is a flow diagram illustrating a process for identifying handwritten characters on an image;

FIG. **10** is a representation of a 28×28 pixel cluster image that is generated by the process shown in FIG. **9**; and

FIG. **11** is an illustration of a neural network that can be used in a character classification model in the process shown in FIG. **9**.

DETAILED DESCRIPTION OF THE EMBODIMENTS

The following discussion of the embodiments of the disclosure directed to a system and method for identifying handwritten characters on an image using a classification model that employs a neural network, where the system and method identify clusters of non-white pixels in the image at a location having handwritten text, and where each cluster is presumed to be a handwritten character, and where the processor employs constraints so that separate clusters are not identified in a stacked up/down direction relative to a writing direction of the handwritten text, that limits a size of each cluster to be less than a predetermined size and/or that requires all of the clusters to be within a certain percentage size of each other is merely exemplary in nature, and is in no way intended to limit the disclosure or its applications or uses.

Embodiments of the present disclosure will now be described more fully hereinafter with reference to the accompanying drawings, in which some, but not all, embodiments of the disclosure are shown. Indeed, the disclosure may be embodied in many different forms and should not be construed as limited to the embodiments set forth herein; rather, these embodiments are provided so that this disclosure will satisfy applicable legal requirements. Like numbers refer to like elements throughout. Unless described or implied as exclusive alternatives, features throughout the drawings and descriptions should be taken as cumulative, such that features expressly associated with some particular embodiments can be combined with other embodiments. Unless defined otherwise, technical and scientific terms used herein have the same meaning as commonly understood to one of ordinary skill in the art to which the presently disclosed subject matter pertains.

The exemplary embodiments are provided so that this disclosure will be both thorough and complete, and will fully convey the scope of the disclosure and enable one of ordinary skill in the art to make, use and practice the disclosure.

The terms "coupled," "fixed," "attached to," "communicatively coupled to," "operatively coupled to," and the like refer to both (i) direct connecting, coupling, fixing, attaching, communicatively coupling; and (ii) indirect connecting coupling, fixing, attaching, communicatively coupling via one or more intermediate components or features, unless otherwise specified herein. "Communicatively coupled to" and "operatively coupled to" can refer to physically and/or electrically related components.

Embodiments of the present disclosure described herein, with reference to flowchart illustrations and/or block diagrams of methods or apparatuses (the term "apparatus" includes systems and computer program products), will be understood such that each block of the flowchart illustrations and/or block diagrams, and combinations of blocks in the flowchart illustrations and/or block diagrams, can be implemented by computer program instructions. These computer program instructions may be provided to a processor of a general purpose computer, special purpose computer, or other programmable data processing apparatus to produce a particular machine, such that the instructions, which execute via the processor of the computer or other programmable data processing apparatus, create mechanisms for implementing the functions/acts specified in the flowchart and/or block diagram block or blocks.

These computer program instructions may also be stored in a computer-readable memory that can direct a computer or other programmable data processing apparatus to function in a particular manner, such that the instructions stored in the computer readable memory produce an article of manufacture including instructions, which implement the function/act specified in the flowchart and/or block diagram block or blocks.

The computer program instructions may also be loaded onto a computer or other programmable data processing apparatus to cause a series of operational steps to be performed on the computer or other programmable apparatus to produce a computer implemented process such that the instructions, which execute on the computer or other programmable apparatus, provide steps for implementing the functions/acts specified in the flowchart and/or block diagram block or blocks. Alternatively, computer program implemented steps or acts may be combined with operator or human implemented steps or acts in order to carry out an embodiment of the disclosure.

While certain exemplary embodiments have been described and shown in the accompanying drawings, it is to be understood that such embodiments are merely illustrative of, and not restrictive on, the broad disclosure, and that this disclosure not be limited to the specific constructions and arrangements shown and described, since various other changes, combinations, omissions, modifications and substitutions, in addition to those set forth in the above paragraphs, are possible. Those skilled in the art will appreciate that various adaptations, modifications, and combinations of the herein described embodiments can be configured without departing from the scope and spirit of the disclosure. Therefore, it is to be understood that, within the scope of the included claims, the disclosure may be practiced other than as specifically described herein.

FIG. **1** illustrates a system **10**, such as a banking system, and environment thereof by which a user **18** benefits through use of services and products of an enterprise system **12**. The user **18** accesses services and products by use of one or more user devices, illustrated in separate examples as a computing device **14** and a mobile device **16**, which may be, as non-limiting examples, a smart phone, a portable digital assistant (PDA), a pager, a mobile television, a gaming device, a laptop computer, a camera, a video recorder, an audio/video player, radio, a GPS device, or any combination of the aforementioned, or other portable device with processing and communication capabilities. In the illustrated example, the mobile device **16** is the system **10** as having exemplary elements, the below descriptions of which apply as well to the computing device **14**, which can be, as non-limiting examples, a desktop computer, a laptop computer or other user-accessible computing device.

Furthermore, the user device, referring to either or both of the computing device **14** and the mobile device **16**, may be or include a workstation, a server, or any other suitable device, including a set of servers, a cloud-based application or system, or any other suitable system, adapted to execute, for example any suitable operating system, including Linux, UNIX, Windows, macOS, iOS, Android and any other known operating system used on personal computers, central computing systems, phones, and other devices.

The user **18** can be an individual, a group, or any entity in possession of or having access to the user device, referring to either or both of the computing device **14** and the mobile device **16**, which may be personal or public items. Although the user **18** may be singly represented in some drawings, at least in some embodiments according to these descriptions the user **18** is one of many such that a market or community of users, consumers, customers, business entities, government entities, clubs, and groups of any size are all within the scope of these descriptions.

The user device, as illustrated with reference to the mobile device **16**, includes components such as at least one of each of a processing device **20**, and a memory device **22** for processing use, such as random access memory (RAM), and read-only memory (ROM). The illustrated mobile device **16** further includes a storage device **24** including at least one of a non-transitory storage medium, such as a microdrive, for long-term, intermediate-term, and short-term storage of computer-readable instructions **26** for execution by the processing device **20**. For example, the instructions **26** can include instructions for an operating system and various applications or programs **30**, of which the application **32** is represented as a particular example. The storage device **24** can store various other data items **34**, which can include, as non-limiting examples, cached data, user files such as those for pictures, audio and/or video recordings, files downloaded or received from other devices, and other data items preferred by the user or required or related to any or all of the applications or programs **30**.

The memory device **22** is operatively coupled to the processing device **20**. As used herein, memory includes any computer readable medium to store data, code, or other information. The memory device **22** may include volatile memory, such as volatile RAM including a cache area for the temporary storage of data. The memory device **22** may also include non-volatile memory, which can be embedded and/or may be removable. The non-volatile memory can additionally or alternatively include an electrically erasable programmable read-only memory (EEPROM), flash memory or the like.

The memory device **22** and the storage device **24** can store any of a number of applications that comprise computer-executable instructions and code executed by the processing device **20** to implement the functions of the mobile device **16** described herein. For example, the memory device **22** may include such applications as a conventional web browser application and/or a mobile P2P payment system client application. These applications also typically provide a graphical user interface (GUI) on a display **40** that allows the user **18** to communicate with the mobile device **16**, and, for example, a mobile banking system, and/or other devices or systems. In one embodiment, when the user **18** decides to enroll in a mobile banking program, the user **18** downloads or otherwise obtains the mobile banking system client application from a mobile banking system, for example, the enterprise system **12**, or from a distinct application server. In other embodiments, the user **18** interacts with a mobile banking system via a web browser application in addition to, or instead of, the mobile P2P payment system client application.

The processing device **20**, and other processors described herein, generally include circuitry for implementing communication and/or logic functions of the mobile device **16**. For example, the processing device **20** may include a digital signal processor, a microprocessor, and various analog to digital converters, digital to analog converters, and/or other support circuits. Control and signal processing functions of the mobile device **16** are allocated between these devices according to their respective capabilities. The processing device **20** thus may also include the functionality to encode and interleave messages and data prior to modulation and transmission. The processing device **20** can additionally include an internal data modem. Further, the processing device **20** may include functionality to operate one or more software programs, which may be stored in the memory device **22**, or in the storage device **24**. For example, the processing device **20** may be capable of operating a connectivity program, such as a web browser application. The web browser application may then allow the mobile device **16** to transmit and receive web content, such as, for example, location-based content and/or other web page content, according to a wireless application protocol (WAP), hypertext transfer protocol (HTTP), and/or the like.

The memory device **22** and the storage device **24** can each also store any of a number of pieces of information, and data, used by the user device and the applications and devices that facilitate functions of the user device, or are in communication with the user device, to implement the functions described herein and others not expressly described. For example, the storage device **24** may include such data as user authentication information, etc.

The processing device **20**, in various examples, can operatively perform calculations, can process instructions for execution and can manipulate information. The processing device **20** can execute machine-executable instructions stored in the storage device **24** and/or the memory device **22** to thereby perform methods and functions as described or implied herein, for example, by one or more corresponding flow charts expressly provided or implied as would be understood by one of ordinary skill in the art to which the subject matters of these descriptions pertain. The processing device **20** can be or can include, as non-limiting examples, a central processing unit (CPU), a microprocessor, a graphics processing unit (GPU), a microcontroller, an application-specific integrated circuit (ASIC), a programmable logic device (PLD), a digital signal processor (DSP), a field programmable gate array (FPGA), a state machine, a controller, gated or transistor logic, discrete physical hardware components, and combinations thereof. In some embodiments, particular portions or steps of methods and functions described herein are performed in whole or in part by way of the processing device **20**, while in other embodiments methods and functions described herein include cloud-based computing in whole or in part such that the processing device **20** facilitates local operations including, as non-limiting examples, communication, data transfer, and user inputs and outputs such as receiving commands from and providing displays to the user.

The mobile device **16**, as illustrated, includes an input and output system **36**, referring to, including, or operatively coupled with, user input devices and user output devices, which are operatively coupled to the processing device **20**. The user output devices include the display **40** (e.g., a liquid crystal display or the like), which can be, as a non-limiting example, a touch screen of the mobile device **16**, which serves both as an output device, by providing graphical and text indicia and presentations for viewing by one or more of the users **18**, and as an input device, by providing virtual buttons, selectable options, a virtual keyboard, and other indicia that, when touched, control the mobile device **16** by user action. The user output devices include a speaker **44** or other audio device. The user input devices, which allow the mobile device **16** to receive data and actions such as button manipulations and touches from a user such as the user **18**, may include any of a number of devices allowing the mobile device **16** to receive data from a user, such as a keypad, keyboard, touch-screen, touchpad, microphone **42**, mouse, joystick, other pointer device, button, soft key, and/or other input device(s). The user interface may also include a camera **46**, such as a digital camera.

Further non-limiting examples include one or more of each, any and all of a wireless or wired keyboard, a mouse, a touchpad, a button, a switch, a light, an LED, a buzzer, a bell, a printer and/or other user input devices and output devices for use by or communication with the user **18** in accessing, using, and controlling, in whole or in part, the user device, referring to either or both of the computing device **14** and the mobile device **16**. Inputs by one or more of the users **18** can thus be made via voice, text or graphical indicia selections. For example, such inputs in some examples correspond to user-side actions and communications seeking services and products of the enterprise system **12**, and at least some outputs in such examples correspond to data representing enterprise-side actions and communications in two-way communications between the user **18** and the enterprise system **12**.

The mobile device **16** may also include a positioning system device **48**, which can be, for example, a global positioning system (GPS) device configured to be used by a positioning system to determine a location of the mobile device **16**. For example, the positioning system device **48** may include a GPS transceiver. In some embodiments, the positioning system device **48** includes an antenna, transmitter, and receiver. For example, in one embodiment, triangulation of cellular signals may be used to identify the approximate location of the mobile device **16**. In other embodiments, the positioning device **48** includes a proximity sensor or transmitter, such as an RFID tag, that can sense or be sensed by devices known to be located proximate a merchant or other location to determine that the consumer mobile device **16** is located proximate these known devices.

In the illustrated example, a system intraconnect **38**, connects, for example electrically, the various described, illustrated, and implied components of the mobile device **16**. The intraconnect **38**, in various non-limiting examples, can include or represent, a system bus, a high-speed interface connecting the processing device **20** to the memory device **22**, individual electrical connections among the components, and electrical conductive traces on a motherboard common to some or all of the above-described components of the user device. As discussed herein, the system intraconnect **38** may operatively couple various components with one another, or in other words, electrically connects those components, either directly or indirectly—by way of intermediate component(s)—with one another.

The user device, referring to either or both of the computing device **14** and the mobile device **16**, with particular reference to the mobile device **16** for illustration purposes, includes a communication interface **50**, by which the mobile device **16** communicates and conducts transactions with other devices and systems. The communication interface **50** may include digital signal processing circuitry and may provide two-way communications and data exchanges, for example, wirelessly via wireless communication device **52**, and for an additional or alternative example, via wired or docked communication by mechanical electrically conductive connector **54**. Communications may be conducted via various modes or protocols, of which GSM voice calls, SMS, EMS, MMS messaging, TDMA, CDMA, PDC, WCDMA, CDMA2000, and GPRS, are all non-limiting and non-exclusive examples. Thus, communications can be conducted, for example, via the wireless communication device **52**, which can be or include a radio-frequency transceiver, a Bluetooth device, Wi-Fi device, a near-field communication device, and other transceivers. In addition, GPS may be included for navigation and location-related data exchanges, ingoing and/or outgoing. Communications may also or alternatively be conducted via the connector **54** for wired connections such by USB, Ethernet, and other physically connected modes of data transfer.

The processing device **20** is configured to use the communication interface **50** as, for example, a network interface to communicate with one or more other devices on a network. In this regard, the communication interface **50** utilizes the wireless communication device **52** as an antenna operatively coupled to a transmitter and a receiver (together a "transceiver") included with the communication interface **50**. The processing device **20** is configured to provide signals to and receive signals from the transmitter and receiver, respectively. The signals may include signaling information in accordance with the air interface standard of the applicable cellular system of a wireless telephone network. In this regard, the mobile device **16** may be configured to operate with one or more air interface standards, communication protocols, modulation types, and access types. By way of illustration, the mobile device **16** may be configured to operate in accordance with any of a number of first, second, third, fourth or fifth-generation communication protocols and/or the like. For example, the mobile device **16** may be configured to operate in accordance with second-generation (2G) wireless communication protocols IS-136 (time division multiple access (TDMA)), GSM (global system for mobile communication), and/or IS-95 (code division multiple access (CDMA)), or with third-generation (3G) wireless communication protocols, such as universal mobile telecommunications System (UMTS), CDMA2000, wideband CDMA (WCDMA) and/or time division-synchronous CDMA (TD-SCDMA), with fourth-generation (4G) wireless communication protocols such as long-term evolution (LTE), fifth-generation (5G) wireless communication protocols, Bluetooth low energy (BLE) communication protocols such as Bluetooth 5.0, ultra-wideband (UWB) communication protocols, and/or the like. The mobile device **16** may also be configured to operate in accordance with non-cellular communication mechanisms, such as via a wireless local area network (WLAN) or other communication/data networks.

The communication interface **50** may also include a payment network interface. The payment network interface may include software, such as encryption software, and hardware, such as a modem, for communicating information to and/or from one or more devices on a network. For example, the mobile device **16** may be configured so that it can be used as a credit or debit card by, for example, wirelessly communicating account numbers or other authentication information to a terminal of the network. Such communication could be performed via transmission over a wireless communication protocol such as the Near-field communication protocol.

The mobile device **16** further includes a power source **28**, such as a battery, for powering various circuits and other devices that are used to operate the mobile device **16**. Embodiments of the mobile device **16** may also include a clock or other timer configured to determine and, in some cases, communicate actual or relative time to the processing device **20** or one or more other devices. For a further example, the clock may facilitate timestamping transmissions, receptions, and other data for security, authentication, logging, polling, data expiry and forensic purposes.

The system **10** as illustrated diagrammatically represents at least one example of a possible implementation, where alternatives, additions, and modifications are possible for performing some or all of the described methods, operations and functions. Although shown separately, in some embodiments, two or more systems, servers, or illustrated components may utilized. In some implementations, the functions of one or more systems, servers, or illustrated components may be provided by a single system or server. In some embodiments, the functions of one illustrated system or server may be provided by multiple systems, servers, or computing devices, including those physically located at a central facility, those logically local, and those located as remote with respect to each other.

The enterprise system **12** can offer any number or type of services and products to one or more of the users **18**. In some examples, the enterprise system **12** offers products, and in some examples, the enterprise system **12** offers services. Use of "service(s)" or "product(s)" thus relates to either or both in these descriptions. With regard, for example, to online information and financial services, "service" and "product" are sometimes termed interchangeably. In non-limiting examples, services and products include retail services and products, information services and products, custom services and products, predefined or pre-offered services and products, consulting services and products, advising services and products, forecasting services and products, internet products and services, social media, and financial services and products, which may include, in non-limiting examples, services and products relating to banking, checking, savings, investments, credit cards, automatic-teller machines, debit cards, loans, mortgages, personal accounts, business accounts, account management, credit reporting, credit requests and credit scores.

To provide access to, or information regarding, some or all the services and products of the enterprise system **12**, automated assistance may be provided by the enterprise system **12**. For example, automated access to user accounts and replies to inquiries may be provided by enterprise-side automated voice, text, and graphical display communications and interactions. In at least some examples, any number of human agents **60**, can be employed, utilized, authorized or referred by the enterprise system **12**. Such human agents **60** can be, as non-limiting examples, point of sale or point of service (POS) representatives, online customer service assistants available to the users **18**, advisors, managers, sales team members, and referral agents ready to route user requests and communications to preferred or particular other agents, human or virtual.

The human agents **60** may utilize agent devices **62** to serve users in their interactions to communicate and take action. The agent devices **62** can be, as non-limiting examples, computing devices, kiosks, terminals, smart devices such as phones, and devices and tools at customer service counters and windows at POS locations. In at least one example, the diagrammatic representation of the components of the mobile device **16** in FIG. **1** applies as well to one or both of the computing device **14** and the agent devices **62**.

The agent devices **62** individually or collectively include input devices and output devices, including, as non-limiting examples, a touch screen, which serves both as an output device by providing graphical and text indicia and presentations for viewing by one or more of the agents **60**, and as an input device by providing virtual buttons, selectable options, a virtual keyboard, and other indicia that, when touched or activated, control or prompt the agent device **62** by action of the attendant agent **60**. Further non-limiting examples include, one or more of each, any, and all of a keyboard, a mouse, a touchpad, a joystick, a button, a switch, a light, an LED, a microphone serving as input device for example for voice input by the human agent **60**, a speaker serving as an output device, a camera serving as an input device, a buzzer, a bell, a printer and/or other user input devices and output devices for use by or communication with the human agent **60** in accessing, using, and controlling, in whole or in part, the agent device **62**.

Inputs by one or more of the human agents **60** can thus be made via voice, text or graphical indicia selections. For example, some inputs received by the agent device **62** in some examples correspond to, control, or prompt enterprise-side actions and communications offering services and products of the enterprise system **12**, information thereof, or access thereto. At least some outputs by the agent device **62** in some examples correspond to, or are prompted by, user-side actions and communications in two-way communications between the user **18** and an enterprise-side human agent **60**.

From a user perspective experience, an interaction in some examples within the scope of these descriptions begins with direct or first access to one or more of the human agents **60** in person, by phone or online for example via a chat session or website function or feature. In other examples, a user is first assisted by a virtual agent **64** of the enterprise system **12**, which may satisfy user requests or prompts by voice, text or online functions, and may refer users to one or more of the human agents **60** once preliminary determinations or conditions are made or met.

The enterprise system **12** includes a computing system **70** having various components, such as a processing device **72** and a memory device **74** for processing use, such as random access memory (RAM) and read-only memory (ROM). The computing system **70** further includes a storage device **76** having at least one non-transitory storage medium, such as a microdrive, for long-term, intermediate-term, and short-term storage of computer-readable instructions **78** for execution by the processing device **72**. For example, the instructions **78** can include instructions for an operating system and various applications or programs **80**, of which an application **82** is represented as a particular example. The storage device **76** can store various other data **84**, which can include, as non-limiting examples, cached data, and files such as those for user accounts, user profiles, account balances, and transaction histories, files downloaded or received from other devices, and other data items preferred by the user or required or related to any or all of the applications or programs **80**.

The computing system **70**, in the illustrated example, also includes an input/output system **86**, referring to, including, or operatively coupled with input devices and output devices such as, in a non-limiting example, agent devices **62**, which have both input and output capabilities.

In the illustrated example, a system intraconnect **88** electrically connects the various above-described components of the computing system **70**. In some cases, the intraconnect **88** operatively couples components to one another, which indicates that the components may be directly or indirectly connected, such as by way of one or more intermediate components. The intraconnect **88**, in various non-limiting examples, can include or represent, a system bus, a high-speed interface connecting the processing device **72** to the memory device **74**, individual electrical connections among the components, and electrical conductive traces on a motherboard common to some or all of the above-described components of the user device.

The computing system **70** includes a communication interface **90** by which the computing system **70** communicates and conducts transactions with other devices and systems. The communication interface **90** may include digital signal processing circuitry and may provide two-way communications and data exchanges, for example wirelessly via wireless device **92**, and for an additional or alternative example, via wired or docked communication by mechanical electrically conductive connector **94**. Communications may be conducted via various modes or protocols, of which GSM voice calls, SMS, EMS, MMS messaging, TDMA, CDMA, PDC, WCDMA, CDMA2000, and GPRS, are all non-limiting and non-exclusive examples. Thus, communications can be conducted, for example, via the wireless device **92**, which can be or include a radio-frequency transceiver, a Bluetooth device, Wi-Fi device, near-field communication device, and other transceivers. In addition, GPS may be included for navigation and location-related data exchanges, ingoing and/or outgoing. Communications may also or alternatively be conducted via the connector **94** for wired connections such as by USB, Ethernet, and other physically connected modes of data transfer.

The processing device **72**, in various examples, can operatively perform calculations, can process instructions for execution, and can manipulate information. The processing device **72** can execute machine-executable instructions stored in the storage device **76** and/or the memory device **74** to thereby perform methods and functions as described or implied herein, for example by one or more corresponding flow charts expressly provided or implied as would be understood by one of ordinary skill in the art to which the subjects matters of these descriptions pertain. The processing device **72** can be or can include, as non-limiting examples, a central processing unit (CPU), a microprocessor, a graphics processing unit (GPU), a microcontroller, an application-specific integrated circuit (ASIC), a programmable logic device (PLD), a digital signal processor (DSP), a field programmable gate array (FPGA), a state machine, a controller, gated or transistor logic, discrete physical hardware components, and combinations thereof.

Furthermore, the computing system **70**, may be or include a workstation, a server, or any other suitable device, including a set of servers, a cloud-based application or system, or any other suitable system, adapted to execute, for example any suitable operating system, including Linux, UNIX, Windows, macOS, iOS, Android, and any known other operating system used on personal computer, central computing systems, phones, and other devices.

The user devices, referring to either or both of the mobile device **16** and the computing device **14**, the agent devices **62** and the computing system **70**, which may be one or any number centrally located or distributed, are in communication through one or more networks, referenced as system **10** in FIG. **1**.

The network **100** provides wireless or wired communications among the components of the network **100** and the environment thereof, including other devices local or remote to those illustrated, such as additional mobile devices, servers, and other devices communicatively coupled to the network **100**, including those not illustrated in FIG. **1**. The network **100** is singly depicted for illustrative convenience, but may include more than one network without departing from the scope of these descriptions. In some embodiments, the network **100** may be or provide one or more cloud-based services or operations. The network **100** may be or include an enterprise or secured network, or may be implemented, at least in part, through one or more connections to the Internet. A portion of the network **100** may be a virtual private network (VPN) or an Intranet. The network **100** can include wired and wireless links, including, as non-limiting examples, 802.11a/b/g/n/ac, 802.20, WiMax, LTE, and/or any other wireless link. The network **100** may include any internal or external network, networks, sub-network, and combinations of such operable to implement communications between various computing components within and beyond the network **100**. The network **100** may communicate, for example, internet protocol (IP) packets, frame relay frames, asynchronous transfer mode (ATM) cells, voice, video, data, and other suitable information between network addresses. The network **100** may also include one or more local area networks (LANs), radio access networks (RANs), metropolitan area networks (MANs), wide area networks (WANs), all or a portion of the internet and/or any other communication system or systems at one or more locations.

Two external systems **102** and **104** are illustrated in FIG. **1** and representing any number and variety of data sources, users, consumers, customers, business entities, banking systems, government entities, clubs, and groups of any size are all within the scope of the descriptions. In at least one example, the external systems **102** and **104** represent automatic teller machines (ATMs) utilized by the enterprise system **12** in serving the users **18**. In another example, the external systems **102** and **104** represent payment clearinghouse or payment rail systems for processing payment transactions, and in another example, the external systems **102** and **104** represent third party systems such as merchant systems configured to interact with the user device **16** during transactions and also configured to interact with the enterprise system **12** in back-end transactions clearing processes.

In certain embodiments, one or more of the systems such as the user device **16**, the enterprise system **12**, and/or the external systems **102** and **104** are, include, or utilize virtual resources. In some cases, such virtual resources are considered cloud resources or virtual machines. Such virtual resources may be available for shared use among multiple distinct resource consumers and in certain implementations, virtual resources do not necessarily correspond to one or more specific pieces of hardware, but rather to a collection of pieces of hardware operatively coupled within a cloud computing configuration so that the resources may be shared as needed.

As used herein, an artificial intelligence system, artificial intelligence algorithm, artificial intelligence module, program, and the like, generally refer to computer implemented programs that are suitable to simulate intelligent behavior (i.e., intelligent human behavior) and/or computer systems and associated programs suitable to perform tasks that typically require a human to perform, such as tasks requiring visual perception, speech recognition, decision-making, translation, and the like. An artificial intelligence system may include, for example, at least one of a series of associated if-then logic statements, a statistical model suitable to map raw sensory data into symbolic categories and the like, or a machine learning program. A machine learning program, machine learning algorithm, or machine learning module, as used herein, is generally a type of artificial intelligence including one or more algorithms that can learn and/or adjust parameters based on input data provided to the algorithm. In some instances, machine learning programs, algorithms and modules are used at least in part in implementing artificial intelligence (AI) functions, systems and methods.

Artificial Intelligence and/or machine learning programs may be associated with or conducted by one or more processors, memory devices, and/or storage devices of a computing system or device. It should be appreciated that the artificial intelligence algorithm or program may be incorporated within the existing system architecture or be configured as a standalone modular component, controller, or the like communicatively coupled to the system. An artificial intelligence program and/or machine learning program may generally be configured to perform methods and functions as described or implied herein, for example by one or more corresponding flow charts expressly provided or implied as would be understood by one of ordinary skill in the art to which the subjects matters of these descriptions pertain.

A machine learning program may be configured to implement stored processing, such as decision tree learning, association rule learning, artificial neural networks, recurrent artificial neural networks, long short term memory networks, inductive logic programming, support vector machines, clustering, Bayesian networks, reinforcement learning, representation learning, similarity and metric learning, sparse dictionary learning, genetic algorithms, k-nearest neighbor (KNN), and the like. In some embodiments, the machine learning algorithm may include one or more image recognition algorithms suitable to determine one or more categories to which an input, such as data communicated from a visual sensor or a file in JPEG, PNG or other format, representing an image or portion thereof, belongs. Additionally or alternatively, the machine learning algorithm may include one or more regression algorithms configured to output a numerical value given an input. Further, the machine learning may include one or more pattern recognition algorithms, e.g., a module, subroutine or the like capable of translating text or string characters and/or a speech recognition module or subroutine. In various embodiments, the machine learning module may include a machine learning acceleration logic, e.g., a fixed function matrix multiplication logic, in order to implement the stored processes and/or optimize the machine learning logic training and interface.

One type of algorithm suitable for use in machine learning modules as described herein is an artificial neural network or neural network, taking inspiration from biological neural networks. An artificial neural network can learn to perform tasks by processing examples, without being programmed with any task-specific rules. A neural network generally includes connected units, neurons, or nodes (e.g., connected by synapses) and may allow for the machine learning program to improve performance. A neural network may define a network of functions, which have a graphical relationship. As an example, a feedforward network may be utilized, such as an acyclic graph with nodes arranged in layers.

The artificial intelligence systems and structures discussed herein may employ deep learning. Deep learning is a particular type of machine learning that provides greater learning performance by representing a certain real-world environment as a hierarchy of increasing complex concepts. Deep learning typically employs a software structure comprising several layers of neural networks that perform nonlinear processing, where each successive layer receives an output from the previous layer. Generally, the layers include an input layer that receives raw data from a sensor, a number of hidden layers that extract abstract features from the data, and an output layer that identifies a certain thing based on the feature extraction from the hidden layers. The neural networks include neurons or nodes that each has a "weight" that is multiplied by the input to the node to obtain a probability of whether something is correct. More specifically, each of the nodes has a weight that is a floating point number that is multiplied with the input to the node to generate an output for that node that is some proportion of the input. The weights are initially "trained" or set by causing the neural networks to analyze a set of known data under supervised processing and through minimizing a cost function to allow the network to obtain the highest probability of a correct output. Deep learning neural networks are often employed to provide image feature extraction and transformation for the visual detection and classification of objects in an image, where a video or stream of images can be analyzed by the network to identify and classify objects and learn through the process to better recognize the objects. Thus, in these types of networks, the system can use the same processing configuration to detect certain objects and classify them differently based on how the algorithm has learned to recognize the objects.

FIG. **2** illustrates a feedforward neural network **110** that includes a hidden layer **114** between an input layer **112** and an output layer **116**. The input layer **112**, having nodes commonly referenced in FIG. **2** as input nodes **118** for convenience, communicates input data, variables, matrices, or the like to the hidden layer **114**, having nodes **120**. The hidden layer **114** generates a representation and/or transformation of the input data into a form that is suitable for generating output data. Adjacent layers of the neural network **110** are connected at the edges of the nodes of the respective layers, but nodes within a layer typically are not separated by an edge. In at least one embodiment of such a feedforward neural network, data is communicated to the nodes **118** of the input layer **112**, which then communicates the data to the hidden layer **114**. The hidden layer **114** may be configured to determine the state of the nodes in the respective layers and assign weight coefficients or parameters of the nodes based on the edges separating each of the layers, such as an activation function implemented between the input data communicated from the input layer **112** and the output data communicated to nodes **122** of the output layer **116**. It should be appreciated that the form of the output from the neural network may generally depend on the type of model represented by the algorithm. Although the feedforward neural network **110** expressly includes a single hidden layer, other embodiments of feedforward networks within the scope of the descriptions can include any number of hidden layers. The hidden layers are intermediate the input and output layers and are generally where all or most of the computation is done.

Neural networks may perform a supervised learning process where known inputs and known outputs are utilized to categorize, classify, or predict a quality of a future input. However, additional or alternative embodiments of the machine learning program may be trained utilizing unsupervised or semi-supervised training, where none of the outputs or some of the outputs are unknown, respectively. Typically, a machine learning algorithm is trained, for example, utilizing a training data set, prior to modeling the problem with which the algorithm is associated. Supervised training of the neural network may include choosing a network topology suitable for the problem being modeled by the network and providing a set of training data representative of the problem. Generally, the machine learning algorithm may adjust the weight coefficients until any error in the output data generated by the algorithm is less than a predetermined, acceptable level. For instance, the training process may include comparing the generated output produced by the network in response to the training data with a desired or correct output. An associated error amount may then be determined for the generated output data, such as for each output data point generated in the output layer. The associated error amount may be communicated back through the system as an error signal, where the weight coefficients assigned in the hidden layer are adjusted based on the error signal. For instance, the associated error amount, such as a value between −1 and 1, may be used to modify the previous coefficient, e.g., a propagated value. The machine learning algorithm may be considered sufficiently trained when the associated error amount for the output data is less than the predetermined, acceptable level, for example, each data point within the output layer includes an error amount less than the predetermined, acceptable level. Thus, the parameters determined from the training process can be utilized with new input data to categorize, classify, and/or predict other values based on the new input data.

An additional or alternative type of neural network suitable for use in a machine learning program and/or module is a convolutional neural network (CNN). A CNN is a type of feedforward neural network that may be utilized to model data associated with input data having a grid-like topology. In some embodiments, at least one layer of a CNN may include a sparsely connected layer, in which each output of a first hidden layer does not interact with each input of the next hidden layer. For example, the output of the convolution in the first hidden layer may be an input of the next hidden layer, rather than a respective state of each node of the first layer. CNNs are typically trained for pattern recognition, such as speech processing, language processing, and visual processing. As such, CNNs may be particularly useful for implementing optical and pattern recognition programs required from the machine learning program. A CNN includes an input layer, a hidden layer, and an output layer, typical of feedforward networks, but the nodes of a CNN input layer are generally organized into a set of categories via feature detectors and based on the receptive fields of the sensor, retina, input layer, etc. Each filter may then output data from its respective nodes to corresponding nodes of a subsequent layer of the network. A CNN may be configured to apply the convolution mathematical operation to the respective nodes of each filter and communicate the same to the corresponding node of the next subsequent layer. As an example, the input to the convolution layer may be a multidimensional array of data. The convolution layer, or hidden layer, may be a multidimensional array of parameters determined while training the model.

FIG. **3** is an illustration of an exemplary CNN **130** that includes an input layer **132** and an output layer **134**. However, where the single hidden layer **114** is provided in the network **110**, multiple consecutive hidden layers **136**, **138** and **140** are provided in the CNN **130**. Edge neurons **142** represented by white-filled arrows highlight that hidden layer nodes **144** can be connected locally, such that not all of the nodes of succeeding layers are connected by neurons.

FIG. **4** shows a portion of the CNN **130**, specifically portions of the input layer **132** and the first hidden layer **136**, and illustrates that connections can be weighted. In the illustrated example, labels W**1** and W**2** refer to respective assigned weights for the referenced connections. The two hidden nodes **146** and **148** share the same set of weights W**1** and W**2** when connecting to two local patches.

A weight defines the impact a node in any given layer has on computations by a connected node in the next layer. FIG. **5** shows a network **150** including a node **152** in a hidden layer. The node **152** is connected to several nodes in the previous layer representing inputs to the node **152**. Input nodes **154**, **156**, **158** and **160** in an input layer **162** are each assigned a respective weight W**01**, W**02**, W**03**, and W**04** in the computation at the node **152**, which in this example is a weighted sum.

An additional or alternative type of feedforward neural network suitable for use in the machine learning program and/or module is a recurrent neural network (RNN). An RNN may allow for analysis of sequences of inputs rather than only considering the current input data set. RNNs typically include feedback loops/connections between layers of the topography, thus allowing parameter data to be communicated between different parts of the neural network. RNNs typically have an architecture including cycles, where past values of a parameter influence the current calculation of the parameter, e.g., at least a portion of the output data from the RNN may be used as feedback/input in calculating subsequent output data. In some embodiments, the machine learning module may include an RNN configured for language processing, e.g., an RNN configured to perform statistical language modeling to predict the next word in a string based on the previous words. The RNN(s) of the machine learning program may include a feedback system suitable to provide the connection(s) between subsequent and previous layers of the network.

FIG. **6** illustrates an RNN **170** that includes an input layer **172** with nodes **174**, an output layer **176** with nodes **178**, and multiple consecutive hidden layers **180** and **182** with nodes **184** and nodes **186**, respectively. The RNN **170** also includes a feedback connector **188** configured to communicate parameter data from at least one of the nodes **186** in the second hidden layer **184** to at least one of the nodes **182** in the first hidden layer **184**. It should be appreciated that two or more and up to all of the nodes of a subsequent layer may provide or communicate a parameter or other data to a previous layer of the RNN **170**. Moreover and in some embodiments, the RNN **170** may include multiple feedback connectors, such as connectors suitable to communicatively couple pairs of nodes and/or connector systems configured to provide communication between three or more nodes. Additionally or alternatively, the feedback connector **188** may communicatively couple two or more nodes having at least one hidden layer between them, i.e., nodes of non-sequential layers of the RNN **170**.

In an additional or alternative embodiment, the machine learning program may include one or more support vector machines. A support vector machine may be configured to determine a category to which input data belongs. For example, the machine learning program may be configured to define a margin using a combination of two or more of the input variables and/or data points as support vectors to maximize the determined margin. Such a margin may generally correspond to a distance between the closest vectors that are classified differently. The machine learning program may be configured to utilize a plurality of support vector machines to perform a single classification. For example, the machine learning program may determine the category to which input data belongs using a first support vector determined from first and second data points/variables, and the machine learning program may independently categorize the input data using a second support vector determined from third and fourth data points/variables. The support vector machine(s) may be trained similarly to the training of neural networks, e.g., by providing a known input vector (including values for the input variables) and a known output classification. The support vector machine is trained by selecting the support vectors and/or a portion of the input vectors that maximize the determined margin.

As depicted, and in some embodiments, the machine learning program may include a neural network topography having more than one hidden layer. In such embodiments, one or more of the hidden layers may have a different number of nodes and/or the connections defined between layers. In some embodiments, each hidden layer may be configured to perform a different function. As an example, a first layer of the neural network may be configured to reduce a dimensionality of the input data, and a second layer of the neural network may be configured to perform statistical programs on the data communicated from the first layer. In various embodiments, each node of the previous layer of the network may be connected to an associated node of the subsequent layer (dense layers). Generally, the neural network(s) of the machine learning program may include a relatively large number of layers, e.g., three or more layers, and are referred to as deep neural networks. For example, the node of each hidden layer of a neural network may be associated with an activation function utilized by the machine learning program to generate an output received by a corresponding node in the subsequent layer. The last hidden layer of the neural network communicates a data set (e.g., the result of data processed within the respective layer) to the output layer. Deep neural networks may require more computational time and power to train, but the additional hidden layers provide multistep pattern recognition capability and/or reduced output error relative to simple or shallow machine learning architectures (e.g., including only one or two hidden layers).

FIG. **7** is a block diagram of an artificial intelligence programming system **200** including an AI processor **202**, such as a dedicated processing device, that operates an artificial intelligence program, where the processor **202** includes a front-end sub-processor **204** and a back-end sub-processor **206**. The algorithms associated with the front-end sub-processor **204** and the back-end sub-processor **206** may be stored in an associated memory device and/or storage device, such as memory device **208** communicatively coupled to the AI processor **202**, as shown. Additionally, the system **200** may include a memory **212** storing one or more instructions necessary for operating the AI program. In this embodiment, the sub-processor **204** includes neural networks **214** and **216** operating an AI algorithm **218**, such as feature recognition, and the sub-processor **206** includes neural networks **220** and **222** operating an AI algorithm **224** to perform an operation on the data set communicated directly or indirectly to the sub-processor **206**.

The system **200** may provide statistical models or machine learning programs such as decision tree learning, associate rule learning, recurrent artificial neural networks, support vector machines, and the like. In various embodiments, the sub-processor **204** may be configured to include built in training and inference logic or suitable software to train the neural network prior to use, for example, machine learning logic including, but not limited to, image recognition, mapping and localization, autonomous navigation, speech synthesis, document imaging, or language translation. For example, the sub-processor **204** may be used for image recognition, input categorization, and/or support vector training. In various embodiments, the sub-processor **206** may be configured to implement input and/or model classification, speech recognition, translation, and the like.

For instance and in some embodiments, the system **200** may be configured to perform unsupervised learning, in which the machine learning program performs the training process using unlabeled data, e.g., without known output data with which to compare. During such unsupervised learning, the neural network may be configured to generate groupings of the input data and/or determine how individual input data points are related to the complete input data set. For example, unsupervised training may be used to configure a neural network to generate a self-organizing map, reduce the dimensionally of the input data set, and/or to perform outlier/anomaly determinations to identify data points in the data set that falls outside the normal pattern of the data. In some embodiments, the system **200** may be trained using a semi-supervised learning process in which some but not all of the output data is known, e.g., a mix of labeled and unlabeled data having the same distribution.

In some embodiments, the system **200** may include an index of basic operations, subroutines, and the like (primitives) typically implemented by AI and/or machine learning algorithms. Thus, the system **200** may be configured to utilize the primitives of the processor **202** to perform some or all of the calculations required by the system **200**. Primitives suitable for inclusion in the processor **202** include operations associated with training a convolutional neural network (e.g., pools), tensor convolutions, activation functions, basic algebraic subroutines and programs (e.g., matrix operations, vector operations), numerical method subroutines and programs, and the like.

It should be appreciated that the machine learning program may include variations, adaptations, and alternatives suitable to perform the operations necessary for the system, and the present disclosure is equally applicable to such suitably configured machine learning and/or artificial intelligence programs, modules, etc. For instance, the machine learning program may include one or more long short-term memory (LSTM) RNNs, convolutional deep belief networks, deep belief networks DBNs, and the like. DBNs, for instance, may be utilized to pre-train the weighted characteristics and/or parameters using an unsupervised learning process. Further, the machine learning module may include one or more other machine learning tools (e.g., logistic regression (LR), Naive-Bayes, random forest (RF), matrix factorization, and support vector machines) in addition to, or as an alternative to, one or more neural networks, as described herein.

FIG. **8** is a flow chart diagram **230** showing an exemplary method for model development and deployment by machine learning. The method represents at least one example of a machine learning workflow in which steps are implemented in a machine learning project. At box **232**, a user authorizes, requests, manages, or initiates the machine-learning workflow. This may represent a user such as human agent, or customer, requesting machine-learning assistance or AI functionality to simulate intelligent behavior, such as a virtual agent, or other machine-assisted or computerized tasks that may, for example, entail visual perception, speech recognition, decision-making, translation, forecasting, predictive modelling, and/or suggestions as non-limiting examples. In a first iteration from the user perspective, the box **232** can represent a starting point. However, with regard to continuing or improving an ongoing machine learning workflow, the box **232** can represent an opportunity for further user input or oversight via a feedback loop.

At box **234**, data is received, collected, accessed or otherwise acquired and entered as can be termed data ingestion. At box **236**, data ingested from the box **234** is pre-processed, for example, by cleaning, and/or transformation such as into a format that the following components can digest. The incoming data may be versioned to connect a data snapshot with the particularly resulting trained model. As newly trained models are tied to a set of versioned data, preprocessing steps are tied to the developed model. If new data is subsequently collected and entered, a new model will be generated. If the preprocessing is updated with newly ingested data, an updated model will be generated. The process at the box **236** can include data validation, which focuses on confirming that the statistics of the ingested data are as expected, such as that data values are within expected numerical ranges, that data sets are within any expected or required categories, and that data comply with any needed distributions such as within those categories. The process can proceed to box **238** to automatically alert the initiating user, other human or virtual agents, and/or other systems, if any anomalies are detected in the data, thereby pausing or terminating the process flow until corrective action is taken.

At box **240**, training test data, such as a target variable value, is inserted into an iterative training and testing loop. At box **242**, model training, a core step of the machine learning work flow, is implemented. A model architecture is trained in the iterative training and testing loop. For example, features in the training test data are used to train the model based on weights and iterative calculations in which the target variable may be incorrectly predicted in an early iteration as determined by comparison at box **244**, where the model is tested. Subsequent iterations of the model training at the box **242** may be conducted with updated weights in the calculations.

When compliance and/or success in the model testing at the box **244** is achieved, the process proceeds to box **246**, where model deployment is triggered. The model may be utilized in AI functions and programming, for example, to simulate intelligent behavior, to perform machine-assisted or computerized tasks, of which visual perception, speech recognition, decision-making, translation, forecasting, predictive modelling, and/or automated suggestion generation serve as non-limiting examples.

FIG. **9** is a flow diagram **250** illustrating a process for identifying handwritten characters on an image that has application for automatically identifying the payee on an image of a handwritten check when it is processed by a bank. A scanned image **252** of a check being processed is received by the bank from, for example, the ACH. The image **252** of the check includes a signature line **254**, a payee line **256**, a payor line **258** and a date line **260**. The image **252** is subjected to an optical character recognition (OCR) algorithm at box **262** that reads and converts typed and/or printed text on the image **252** into machine encoded text in a manner well understood by those skilled in the art. One suitable OCR algorithm for this purpose is known as Tesseract™, which is a Python™ algorithm, although others may be equally applicable. These types of known OCR algorithms are able to read and convert typed text in the image **252** with a high degree of accuracy or confidence, but can only read and convert handwritten text with a low and unacceptable accuracy or confidence. One of those typed text portions on a conventional check is the words "pay to the order of" positioned next to the payee line **256** of the check. The OCR algorithm is programmed to identify the location of the words "pay to the order of", or some other suitable typed text in the image **252**, and then using that location to provide the x and y coordinates of the pixels in the image **252** for the location of the payee line **256** in the image **252** so that the area of the image **252** having the handwritten payee can be further processed using a more accurate character recognition process to identify the payee, as will be discussed below. The typed text identified in other areas of the image **252**, such as the routing number, account number, etc. can also be processed for other purposes, if desired, such as for identifying fraud issues.

The image **252** is then subjected to a density-based clustering algorithm that provides character segmentation at box **264** that also receives the location of the payee line **256** in the image **252**. The clustering algorithm identifies clusters of non-white pixels in the area of the image **252** identified by the OCR algorithm, where each separately identified cluster may be a handwritten character that is part of the payee handwritten in the payee line **256**. Particularly, the section of the image **252** being looked at is processed as a matrix of pixels, where each non-white pixel is considered a data point for the clustering process. One suitable density-based clustering algorithm is DBScan™, which is a density-based clustering non-parametric algorithm. Given a set of points in some space, the DBScan™ algorithm groups together points that are closely packed together, i.e., points with many nearby neighbors, marking as outliers points that lie alone in low-density regions whose nearest neighbors are too far away. The output of the clustering algorithm is a dataset array that digitally identifies the x and y coordinates of the pixels in each identified character cluster along with an assigned label for each cluster, where the algorithm will assign the same cluster label to data points that are part of the same cluster.

The clustering algorithm is effective for identifying clusters of pixels in the image **252** that are part of the same character. However, some letters, such as, for example, capital I, may look like two clusters to the algorithm because of the top and bottom bars in the letter. Handwriting heuristics can be employed to add constraints to the clustering algorithm to reduce the chance that more than one cluster dataset array is identified for the same character and/or one cluster dataset includes more than one character. For example, since the payee will be written from left to right on the check, the clustering algorithm could be designed with a constraint where clusters cannot be stacked top to bottom on the check relative to the handwriting direction of the payee. In other words, if two clusters are identified in a vertical direction at the same left to right location on the image **252**, then that cluster can be considered a single cluster for one character. Further, a limit to the size or area of the cluster can also be a constraint. For example, if the size of the cluster exceeds some threshold, then it is assumed that the cluster includes more than one character and the clustering of that cluster can be further defined and processed to identify the multiple clusters. In other words, a constraint can be employed that limits the size of each cluster to be less than a predetermined maximum size. Also, a person will typically write in a manner where all of the characters are about the same size or width. If there is a significant inconsistency in the size of the clusters, then the cluster process can be further refined to identify additional clusters. In other words, a constraint can be employed that requires all of the clusters to be within a certain percentage size of each other.

The dataset array from the clustering algorithm is provided to a cluster extraction and rescaling algorithm at box **266** that extracts the individually identified clusters in the dataset array into individual dataset arrays and rescales each individual dataset array into, for example, a 28×28 pixel cluster image, using extrapolation, which keeps the main features of the image **252**. The rescaling process also centers the cluster in the cluster image and adds border padding. FIG. **10** is a representation of a 28×28 pixel cluster image **274** illustrating an identified cluster for a handwritten letter O after having been processed by the cluster extraction and rescaling algorithm. The size and format of the image **274** is selected to be compatible with a character classification process discussed below.

Each individual cluster image **274** is provided to a character classification model at box **268** that classifies the likelihood that each cluster image **274** is a particular character. The classification model employs a neural network, specifically a CNN, such as neural network **276** shown in

FIG. **11**. The neural network **276** includes an input layer **278** that receives the cluster image **274**, a convolutional layer **280** that classifies the image **274**, a pooling layer **282** that reduces the dimensions of feature maps, a fully connected layer **284** that connects the nodes between layers, and an output layer **286** that outputs the classified characters. The neural network **276** is trained using a known set of training images, where each training image illustrates a letter or a number that has been assigned one of sixty-two character classes, namely, the upper case letters A-Z, the lower case letters a-z and the numbers 0-9. More particularly, nodes in the neural network **276** are weighted and those weights are tuned during the training process to allow the neural network **276** to determine what locations in the image **274** that include non-white pixels are what character. The training process first feeds the neural network **276** character training images and tells the neural network **276** what those characters are, and then feeds the neural network **276** character training images without telling the neural network **276** what the characters are, where the weights are adjusted based on right character identification answers and wrong character identification answers. The known set of training images could be the EMNIST™ dataset, which is a set of 697,932 handwritten character digits derived from the NIST Special Database **19** and converted to a 28×28 pixel image format and dataset structure.

During operation, the neural network **276** determines the likelihood that each image **274** is each of the sixty-two characters, and selects the character with the highest likelihood as the character for that image **274**. The classification model outputs a string of characters from left to right along the payee line **256**, in this example, and identifies spaces between certain characters where non-white pixels do not exist as an indication of a separation between words. The classification model can employ any algorithm suitable for the purposes described herein, such as Pytorch™, which is an open source machine learning framework based on the Torch library, used for applications such as computer vision and natural language processing.

The image **252**, the typed text on the image **252** from the OCR and the character classification and location are sent to a payee identification process at box **270** where the payee is identified to be available to be uploaded to a user's account or transaction register. The classification of the characters may not be 100% accurate, so further operations can be provided to help identify the payee in the event that some of the characters are misidentified. For example, typed zip code and address information on the image **252** can be obtained from the OCR to determine a geographic location of the payee. The payee at that location can be searched using a secondary data source, such as Google Search API™, or some type of autocorrecting function, at box **272** to specifically identify the payee based on the characters that were identified. For example, the identified payee can be automatically searched on the internet to see if it exists, and if so, where.

Particular embodiments and features have been described with reference to the drawings. It is to be understood that these descriptions are not limited to any single embodiment or any particular set of features. Similar embodiments and features may arise or modifications and additions may be made without departing from the scope of these descriptions and the spirit of the appended claims.

What is claimed is:

1. A system for identifying handwritten characters on an image, said system comprising:

a computer including at least one processor and a memory device storing data and executable code that, when executed, causes the at least one processor to:

read and convert typed text on the image to machine encoded text to identify locations of the typed text on the image;

identify a location on the image that includes handwritten text based on the location of predetermined typed text on the image;

identify clusters of non-white pixels in the image at the location having the handwritten text, where each cluster is presumed to be a handwritten character, wherein the at least one processor employs a constraint that limits a size of each cluster to be less than a predetermined size;

generate an individual and separate cluster image for each identified cluster;

classify each cluster image using machine learning and at least one neural network to determine the likelihood that the cluster is a certain character; and

determine what character each cluster image is based on the classification.

2. The system according to claim **1** wherein the at least one processor reads and converts the typed text using an optical character recognition algorithm.

3. The system according to claim **1** wherein the at least one processor identifies clusters of non-white pixels using a density-based clustering algorithm.

4. The system according to claim **1** wherein the at least one processor rescales the cluster when it generates an individual and separate cluster image for each identified cluster.

5. The system according to claim **4** wherein the at least one processor rescales the cluster to a 28×28 pixel cluster image.

6. The system according to claim **1** wherein the at least one processor centers the cluster in the cluster image when it generates an individual and separate cluster image for each identified cluster.

7. The system according to claim **1** wherein the at least one processor classifies each cluster image by determining the likelihood that the cluster image is one of sixty-two character classes, namely, upper case letters A-Z, lower case letters a-z and numbers 0-9.

8. The system according to claim **1** wherein the at least one neural network is a convolutional neural network (CNN).

9. A system for identifying handwritten characters on an image of a check, said system comprising:

a computer including at least one processor and a memory device storing data and executable code that, when executed, causes the at least one processor to:

read and convert typed text on the image to machine encoded text using an optical character recognition algorithm to identify locations of the typed text on the image including identifying the location of the typed words "pay to the order of";

identify a location on the image that includes a handwritten payee based on the location of the typed words "pay to the order of";

identify clusters of non-white pixels in the image at the location having the handwritten payee using a density-based clustering algorithm, where each cluster is presumed to be a handwritten character, wherein the at least one processor employs a constraint that limits a size of each cluster to be less than a predetermined size;

generate an individual and separate cluster image for each identified cluster;

classify each cluster image using machine learning and at least one neural network to determine the likelihood that the cluster is a certain character, wherein the at least one processor classifies each cluster image by determining the likelihood that the cluster image is one of sixty-two character classes, namely, upper case letters A-Z, lower case letters a-z and numbers 0-9; and

determine what character each cluster image is based on the classification.

10. The system according to claim **9** wherein the at least one processor rescales the cluster when it generates an individual and separate cluster image for each identified cluster.

11. The system according to claim **10** wherein the at least one processor rescales the cluster to a 28×28 pixel cluster image.

12. The system according to claim **9** wherein the at least one processor centers the cluster in the cluster image when it generates an individual and separate cluster image for each identified cluster.

13. A method for identifying handwritten characters on an image, said method comprising:

reading and converting typed text on the image to machine encoded text to identify locations of the typed text on the image;

identifying a location on the image that includes handwritten text based on the location of predetermined typed text on the image;

identifying clusters of non-white pixels in the image at the location having the handwritten text, where each cluster is presumed to be a handwritten character, wherein identifying clusters of non-white pixels includes employing that limits a size of each cluster to be less than a predetermined size;

generating an individual and separate cluster image for each identified cluster,

classifying each cluster image using machine learning and at least one neural network to determine the likelihood that the cluster is a certain character; and

determining what character each cluster image is based on the classification.

14. The method according to claim **13** wherein reading and converting the typed text includes using an optical character recognition algorithm and identifying clusters of non-white pixels includes using a density-based clustering algorithm.

15. The method according to claim **13** wherein generating an individual and separate cluster image for each identified cluster includes rescaling each cluster.

16. The method according to claim **15** wherein each cluster is rescaled to a 28×28 pixel cluster image.

17. The method according to claim **13** wherein generating an individual and separate cluster image for each identified cluster includes centering the cluster in the image.

18. The method according to claim **13** wherein classifying each cluster image includes determining the likelihood that the cluster image is one of sixty-two character classes, namely, upper case letters A-Z, lower case letters a-z and numbers 0-9.

19. The method according to claim **13** wherein the at least one neural network is a convolutional neural network (CNN).

20. The method according to claim **13** wherein the image is an image of a check, the predetermined typed text is "pay to the order of" and the handwritten text is a payee on the check.

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