

**SYSTEMS AND METHODS FOR IDENTIFYING DEMENTIA TYPES AND/OR RATE  
OF PROGRESSION USING IMAGING BIOMARKER**

**CROSS-REFERENCE TO RELATED APPLICATIONS**

**[0001]** This application claims priority to U.S. Application No. 63/584,986, filed September 25, 2023, the content of which is incorporated herein by reference in its entirety.

**FEDERALLY SPONSORED RESEARCH OR DEVELOPMENT**

**[0002]** This invention was made with government support under P30 AG066506 awarded by the National Institutes of Health. The government has certain rights in the invention.

**BACKGROUND**

**[0003]** There are many types of dementia, including Alzheimer's dementia, dementia with Lewy bodies, frontotemporal dementia, and others. Often the presenting symptoms of individuals with different types of dementia are too similar for differentiation between different types of dementia based on the individuals' presenting symptoms. Different treatments may be more effective for different types of dementia. Therefore, being able determine what type of dementia and/or rate of progression an individual is experiencing may be beneficial for the treatment of the individual's presenting symptoms and/or slowing disease progression. It can also be beneficial to predict how the dementia changes over time and predict which people will worsen at different rates.

**BRIEF SUMMARY**

**[0004]** Various embodiments provide systems, apparatuses, systems, computer program products, and/or the like for determining and/or identifying a type of dementia and/or rate of progression an individual is experiencing. In various embodiments, information regarding free-water fraction and/or free-water corrected fractional anisotropy (FA<sub>T</sub>) for multiple parts of an individual's brain are extracted from and/or determined based on magnetic resonance imaging (MRI) data for the individual. An individual feature vector is generated based on the information regarding free-water fraction and/or free-water corrected fractional anisotropy (FA<sub>T</sub>) for multiple parts of the individual's brain. A dementia identification and prediction model processes the

individual feature vector and provides output indicating a type of dementia and/or rate of progression.

**[0005]** According to one aspect, a computer-implemented method for determining a type of dementia and predicting how the dementia changes over time is provided. In an example embodiment, the method includes obtaining, by at least one processor, information regarding at least one of free-water fraction or free-water corrected fractional anisotropy (FA<sub>T</sub>) for multiple parts of an individual's brain; generating, by the one or more processors, an individual feature vector based on the information regarding at least one of free-water fraction or free-water corrected fractional anisotropy (FA<sub>T</sub>) for multiple parts of the individual's brain; processing by the one or more processors, the individual feature vector using a machine learning-trained dementia identification and prediction model to obtain a model output indicating a type of dementia and/or rate of progression being experienced by the individual; and providing, by the one or more processors, output indicating the type of dementia and/or rate of progression being experienced by the individual.

**[0006]** According to another aspect, an apparatus configured to determine a type of dementia and/or predicting how the dementia changes over time is provided. In an example embodiment, the apparatus includes at least one processor and a memory storing computer executable instructions. The memory and computer executable instructions configured to, when executed by one or more processors, cause the apparatus to perform at least obtaining information regarding at least one of free-water fraction or free-water corrected fractional anisotropy (FA<sub>T</sub>) for multiple parts of an individual's brain; generating an individual feature vector based on the information regarding at least one of free-water fraction or free-water corrected fractional anisotropy (FA<sub>T</sub>) for multiple parts of the individual's brain; processing the individual feature vector using a machine learning-trained dementia identification and prediction model to obtain a model output indicating a type of dementia and/or rate of progression being experienced by the individual; and providing output indicating the type of dementia and/or rate of progression being experienced by the individual.

**[0007]** According to still another aspect, a computer program product for determining a type of dementia and/or predicting how the dementia changes over time is provided. In an example embodiment, the computer program product comprises at least one non-transitory computer readable storage medium storing computer executable instructions. The computer executable

instructions are configured, when executed by at least one processor of an apparatus, cause the apparatus to perform obtaining information regarding at least one of free-water fraction or free-water corrected fractional anisotropy (FA<sub>T</sub>) for multiple parts of an individual's brain; generating an individual feature vector based on the information regarding at least one of free-water fraction or free-water corrected fractional anisotropy (FA<sub>T</sub>) for multiple parts of the individual's brain; processing the individual feature vector using a machine learning-trained dementia identification and prediction model to obtain a model output indicating a type of dementia and/or rate of progression being experienced by the individual; and providing output indicating the type of dementia and/or rate of progression being experienced by the individual.

### BRIEF DESCRIPTION OF THE DRAWINGS

[0008] Having thus described the invention in general terms, reference will now be made to the accompanying drawings, which are not necessarily drawn to scale, and wherein:

[0009] Fig. 1 is an overview of a system that can be used to practice embodiments of the present invention;

[0010] Fig. 2 is an exemplary schematic diagram of an assessment computing entity according to one embodiment of the present invention;

[0011] Fig. 3 is an exemplary schematic diagram of a user computing entity according to one embodiment of the present invention;

[0012] Fig. 4 provides a flowchart illustrating various processes and/or procedures performed by an assessment computing entity, for example, to determine and provide a type of dementia and/or rate of progression being experienced by an individual based on imaging data of the individual's brain, according to an example embodiment; and

[0013] Fig. 5 provides a flowchart illustrating various processes and/or procedures performed by an assessment computing entity, for example, to determine information regarding the free-water fraction and/or FA<sub>T</sub> for multiple parts of the individual's brain, according to an example embodiment.

### DETAILED DESCRIPTION OF VARIOUS EMBODIMENTS

[0014] Various embodiments of the present invention now will be described more fully hereinafter with reference to the accompanying drawings, in which some, but not all

embodiments of the inventions are shown. Indeed, these inventions 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. The term “or” is used herein in both the alternative and conjunctive sense, unless otherwise indicated. The terms “illustrative” and “exemplary” are used to be examples with no indication of quality level. Like numbers refer to like elements throughout.

### **I. Computer Program Products, Methods, and Computing Entities**

**[0015]** Embodiments of the present invention may be implemented in various ways, including as computer program products that comprise articles of manufacture. A computer program product may include a non-transitory computer-readable storage medium storing applications, programs, program modules, scripts, source code, program code, object code, byte code, compiled code, interpreted code, machine code, executable instructions, and/or the like (also referred to herein as executable instructions, instructions for execution, computer program products, program code, and/or similar terms used herein interchangeably). Such non-transitory computer-readable storage media include all computer-readable media (including volatile and non-volatile media).

**[0016]** In one embodiment, a non-volatile computer-readable storage medium may include a floppy disk, flexible disk, hard disk, solid-state storage (SSS) (e.g., a solid state drive (SSD), solid state card (SSC), solid state module (SSM), enterprise flash drive, magnetic tape, or any other non-transitory magnetic medium, and/or the like. A non-volatile computer-readable storage medium may also include a punch card, paper tape, optical mark sheet (or any other physical medium with patterns of holes or other optically recognizable indicia), compact disc read only memory (CD-ROM), compact disc-rewritable (CD-RW), digital versatile disc (DVD), Blu-ray disc (BD), any other non-transitory optical medium, and/or the like. Such a non-volatile computer-readable storage medium may also include read-only memory (ROM), programmable read-only memory (PROM), erasable programmable read-only memory (EPROM), electrically erasable programmable read-only memory (EEPROM), flash memory (e.g., Serial, NAND, NOR, and/or the like), multimedia memory cards (MMC), secure digital (SD) memory cards, SmartMedia cards, CompactFlash (CF) cards, Memory Sticks, and/or the like. Further, a non-volatile computer-readable storage medium may also include conductive-bridging random access

memory (CBRAM), phase-change random access memory (PRAM), ferroelectric random-access memory (FeRAM), non-volatile random-access memory (NVRAM), magnetoresistive random-access memory (MRAM), resistive random-access memory (RRAM), Silicon-Oxide-Nitride-Oxide-Silicon memory (SONOS), floating junction gate random access memory (FJG RAM), Millipede memory, racetrack memory, and/or the like.

**[0017]** In one embodiment, a volatile computer-readable storage medium may include random access memory (RAM), dynamic random access memory (DRAM), static random access memory (SRAM), fast page mode dynamic random access memory (FPM DRAM), extended data-out dynamic random access memory (EDO DRAM), synchronous dynamic random access memory (SDRAM), double data rate synchronous dynamic random access memory (DDR SDRAM), double data rate type two synchronous dynamic random access memory (DDR2 SDRAM), double data rate type three synchronous dynamic random access memory (DDR3 SDRAM), Rambus dynamic random access memory (RDRAM), Twin Transistor RAM (TTRAM), Thyristor RAM (T-RAM), Zero-capacitor (Z-RAM), Rambus in-line memory module (RIMM), dual in-line memory module (DIMM), single in-line memory module (SIMM), video random access memory (VRAM), cache memory (including various levels), flash memory, register memory, and/or the like. It will be appreciated that where embodiments are described to use a computer-readable storage medium, other types of computer-readable storage media may be substituted for or used in addition to the computer-readable storage media described above.

**[0018]** As should be appreciated, various embodiments of the present invention may also be implemented as methods, apparatus, systems, computing devices, computing entities, and/or the like. As such, embodiments of the present invention may take the form of an apparatus, system, computing device, computing entity, and/or the like executing instructions stored on a computer-readable storage medium to perform certain steps or operations. Thus, embodiments of the present invention may also take the form of an entirely hardware embodiment, an entirely computer program product embodiment, and/or an embodiment that comprises combination of computer program products and hardware performing certain steps or operations.

**[0019]** Embodiments of the present invention are described below with reference to block diagrams and flowchart illustrations. Thus, it should be understood that each block of the block diagrams and flowchart illustrations may be implemented in the form of a computer program product, an entirely hardware embodiment, a combination of hardware and computer program

products, and/or apparatus, systems, computing devices, computing entities, and/or the like carrying out instructions, operations, steps, and similar words used interchangeably (e.g., the executable instructions, instructions for execution, program code, and/or the like) on a computer-readable storage medium for execution. For example, retrieval, loading, and execution of code may be performed sequentially such that one instruction is retrieved, loaded, and executed at a time. In some exemplary embodiments, retrieval, loading, and/or execution may be performed in parallel such that multiple instructions are retrieved, loaded, and/or executed together. Thus, such embodiments can produce specifically configured machines performing the steps or operations specified in the block diagrams and flowchart illustrations. Accordingly, the block diagrams and flowchart illustrations support various combinations of embodiments for performing the specified instructions, operations, or steps.

## **II. Exemplary System Architecture**

[0020] Figure 1 provides an illustration of an exemplary embodiment of the present invention. As shown in Figure 1, this particular embodiment may include one or more imaging machines 115, one or more assessment computing entities 100, one or more networks 105, and one or more user computing entities 110. Each of these components, entities, devices, systems, and similar words used herein interchangeably may be in direct or indirect communication with, for example, one another over the same or different wired or wireless networks. Additionally, while Figure 1 illustrates the various system entities as separate, standalone entities, the various embodiments are not limited to this particular architecture.

### *1. Exemplary Assessment Computing Entity*

[0021] Figure 2 provides a schematic of an assessment computing entity 100 according to one embodiment of the present invention. An assessment computing entity 100 may belong to and/or be operated by a medical facility, hospital, clinic, diagnostic service, and/or the like. However, the assessment computing entity 100 may belong and/or be operated by a third-party computing service that performs remote computations for a medical facility. In an example embodiment, an assessment computing entity 100 may be configured to control one or more

imaging machines 115 and/or to receive imaging information/data from one or more imaging machines and/or a controller computing entity thereof.

**[0022]** In general, the terms computing entity, computer, entity, device, system, and/or similar words used herein interchangeably may refer to, for example, one or more computers, computing entities, desktop computers, mobile phones, tablets, phablets, notebooks, laptops, distributed systems, gaming consoles (e.g., Xbox, Play Station, Wii), watches, glasses, iBeacons, proximity beacons, key fobs, radio frequency identification (RFID) tags, ear pieces, scanners, televisions, dongles, cameras, wristbands, wearable items/devices, kiosks, input terminals, servers or server networks, blades, gateways, switches, processing devices, processing entities, set-top boxes, relays, routers, network access points, base stations, the like, and/or any combination of devices or entities adapted to perform the functions, operations, and/or processes described herein. Such functions, operations, and/or processes may include, for example, transmitting, receiving, operating on, processing, displaying, storing, determining, creating/generating, monitoring, evaluating, comparing, and/or similar terms used herein interchangeably. In one embodiment, these functions, operations, and/or processes can be performed on data, content, information, and/or similar terms used herein interchangeably.

**[0023]** As indicated, in one embodiment, the assessment computing entity 100 may also include one or more communications interfaces 220 for communicating with various computing entities, such as by communicating data, content, information, and/or similar terms used herein interchangeably that can be transmitted, received, operated on, processed, displayed, stored, and/or the like. For instance, the assessment computing entity 100 may communicate with user computing entities 110 and/or a variety of other computing entities.

**[0024]** As shown in Figure 2, in one embodiment, the assessment computing entity 100 may include or be in communication with one or more processing elements 205 (also referred to as processors, processing circuitry, and/or similar terms used herein interchangeably) that communicate with other elements within the assessment computing entity 100 via a bus, for example. As will be understood, the processing element 205 may be embodied in a number of different ways. For example, the processing element 205 may be embodied as one or more complex programmable logic devices (CPLDs), microprocessors, multi-core processors, coprocessing entities, application-specific instruction-set processors (ASIPs), microcontrollers, and/or controllers. Further, the processing element 205 may be embodied as one or more other

processing devices or circuitry. The term circuitry may refer to an entirely hardware embodiment or a combination of hardware and computer program products. Thus, the processing element 205 may be embodied as integrated circuits, application specific integrated circuits (ASICs), field programmable gate arrays (FPGAs), programmable logic arrays (PLAs), hardware accelerators, other circuitry, and/or the like. As will therefore be understood, the processing element 205 may be configured for a particular use or configured to execute instructions stored in volatile or non-volatile media or otherwise accessible to the processing element 205. As such, whether configured by hardware or computer program products, or by a combination thereof, the processing element 205 may be capable of performing steps or operations according to embodiments of the present invention when configured accordingly.

**[0025]** In one embodiment, the assessment computing entity 100 may further include or be in communication with non-volatile media (also referred to as non-volatile storage, memory, memory storage, memory circuitry and/or similar terms used herein interchangeably). In one embodiment, the non-volatile storage or memory may include one or more non-volatile storage or memory media 210, including but not limited to hard disks, ROM, PROM, EPROM, EEPROM, flash memory, MMCs, SD memory cards, Memory Sticks, CBRAM, PRAM, FeRAM, NVRAM, MRAM, RRAM, SONOS, FJG RAM, Millipede memory, racetrack memory, and/or the like. As will be recognized, the non-volatile storage or memory media may store databases, database instances, database management systems, data, applications, programs, program modules, scripts, source code, object code, byte code, compiled code, interpreted code, machine code, executable instructions, and/or the like. The term database, database instance, database management system, and/or similar terms used herein interchangeably may refer to a collection of records or data that is stored in a computer-readable storage medium using one or more database models, such as a hierarchical database model, network model, relational model, entity-relationship model, object model, document model, semantic model, graph model, and/or the like.

**[0026]** In one embodiment, the assessment computing entity 100 may further include or be in communication with volatile media (also referred to as volatile storage, memory, memory storage, memory circuitry and/or similar terms used herein interchangeably). In one embodiment, the volatile storage or memory may also include one or more volatile storage or memory media 215, including but not limited to RAM, DRAM, SRAM, FPM DRAM, EDO DRAM, SDRAM,

DDR SDRAM, DDR2 SDRAM, DDR3 SDRAM, RDRAM, TTRAM, T-RAM, Z-RAM, RIMM, DIMM, SIMM, VRAM, cache memory, register memory, and/or the like. As will be recognized, the volatile storage or memory media may be used to store at least portions of the databases, database instances, database management systems, data, applications, programs, program modules, scripts, source code, object code, byte code, compiled code, interpreted code, machine code, executable instructions, and/or the like being executed by, for example, the processing element 205. Thus, the databases, database instances, database management systems, data, applications, programs, program modules, scripts, source code, object code, byte code, compiled code, interpreted code, machine code, executable instructions, and/or the like may be used to control certain aspects of the operation of the assessment computing entity 100 with the assistance of the processing element 205 and operating system.

**[0027]** In various embodiments, the assessment computing entity 100 is configured to operate and/or cause execution of a machine learning-trained dementia identification and prediction model. In various embodiments, the dementia identification and prediction model is a support vector machine (SVM), a decision tree-based trained model, a naïve Bayes classifier, a neural network-based classifier, a k-nearest neighbors classifier, a feed forward neural network model, a multi-layer perceptron model, a convolutional neural network model, a recurrent neural network model, a long short-term memory network model, a gated recurrent unit model, a radial basis function network model, a capsule network model, a residual neural network model, deep learning model, and/or the like.

**[0028]** For example, in some embodiments, the machine learning-trained dementia identification and prediction model is an SVM configured and/or trained to perform a transformation of a feature vector by learning one or more hyperplanes that distinguishably segregate feature vectors corresponding to different classes. The dementia identification and prediction model may be trained to identify and/or determine one or more hyperplanes that separate different classes with the maximum margin. For example, the dementia identification and prediction model may include an input layer configured to receive a feature vector, one or more hidden layers that transform the feature vector received via the input layer by determining a “location” of a point in a multi-dimensional space corresponding to the feature vector and/or determining a relative location of the point in the multi-dimensional space corresponding to the feature vector with respect to one or more hyperplanes defined during a machine learning

training procedure of the dementia identification and prediction model, and an output layer that converts that location or relative location information determined via the one or more hidden layers into output information. For example, the output information may be a class to which the feature vector is expected to correspond to, a likelihood or probability that that feature vector corresponds to one or more classes, and/or the like. In various embodiments, the assessment computing entity 100 is configured to use a machine learning protocol to train the dementia identification and prediction model and/or to process one or more feature vectors corresponding to respective individuals to determine a dementia type and/or rate of progression for the individuals.

**[0029]** As indicated, in one embodiment, the assessment computing entity 100 may also include one or more communications interfaces 220 for communicating with various computing entities, such as by communicating data, content, information, and/or similar terms used herein interchangeably that can be transmitted, received, operated on, processed, displayed, stored, and/or the like. Such communication may be executed using a wired data transmission protocol, such as fiber distributed data interface (FDDI), digital subscriber line (DSL), Ethernet, asynchronous transfer mode (ATM), frame relay, data over cable service interface specification (DOCSIS), or any other wired transmission protocol. Similarly, the assessment computing entity 100 may be configured to communicate via wireless external communication networks using any of a variety of protocols, such as general packet radio service (GPRS), Universal Mobile Telecommunications System (UMTS), Code Division Multiple Access 2000 (CDMA2000), CDMA2000 1X (1xRTT), Wideband Code Division Multiple Access (WCDMA), Time Division-Synchronous Code Division Multiple Access (TD-SCDMA), Long Term Evolution (LTE), Evolved Universal Terrestrial Radio Access Network (E-UTRAN), Evolution-Data Optimized (EVDO), High Speed Packet Access (HSPA), High-Speed Downlink Packet Access (HSDPA), IEEE 802.11 (Wi-Fi), Wi-Fi Direct, 802.16 (WiMAX), ultra-wideband (UWB), infrared (IR) protocols, near field communication (NFC) protocols, Wibree, Bluetooth protocols, wireless universal serial bus (USB) protocols, and/or any other wireless protocol.

**[0030]** Although not shown, the assessment computing entity 100 may include or be in communication with one or more input elements, such as a keyboard input, a mouse input, a touch screen/display input, motion input, movement input, audio input, pointing device input, joystick input, keypad input, and/or the like. The assessment computing entity 100 may also

include or be in communication with one or more output elements (not shown), such as audio output, video output, screen/display output, motion output, movement output, and/or the like.

**[0031]** As will be appreciated, one or more of the assessment computing entity's 100 components may be located remotely from other assessment computing entity 100 components, such as in a distributed system. Furthermore, one or more of the components may be combined and additional components performing functions described herein may be included in the assessment computing entity 100. Thus, the assessment computing entity 100 can be adapted to accommodate a variety of needs and circumstances. As will be recognized, these architectures and descriptions are provided for exemplary purposes only and are not limiting to the various embodiments.

## 2. Exemplary User Computing Entity

**[0032]** A user may be an individual, a family, a company, an organization, an entity, a department within an organization, a representative of an organization and/or person, and/or the like. In one example, users may be medical personnel, doctors, nurses, patients, and/or the like. For instance, a user may operate a user computing entity 110 that includes one or more components that are functionally similar to those of the assessment computing entity 100. Figure 3 provides an illustrative schematic representative of a user computing entity 110 that can be used in conjunction with embodiments of the present invention. In general, the terms device, system, computing entity, entity, and/or similar words used herein interchangeably may refer to, for example, one or more computers, computing entities, desktops, mobile phones, tablets, phablets, notebooks, laptops, distributed systems, gaming consoles (e.g., Xbox, Play Station, Wii), watches, glasses, key fobs, radio frequency identification (RFID) tags, ear pieces, scanners, cameras, wristbands, kiosks, input terminals, servers or server networks, blades, gateways, switches, processing devices, processing entities, set-top boxes, relays, routers, network access points, base stations, the like, and/or any combination of devices or entities adapted to perform the functions, operations, and/or processes described herein. User computing entities 110 can be operated by various parties. As shown in Figure 3, the user computing entity 110 can include an antenna 312, a transmitter 304 (e.g., radio), a receiver 306 (e.g., radio), and a processing element 308 (e.g., CPLDs, microprocessors, multi-core processors, coprocessing entities, ASIPs,

microcontrollers, and/or controllers) that provides signals to and receives signals from the transmitter 304 and receiver 306, respectively.

**[0033]** The signals provided to and received from the transmitter 304 and the receiver 306, respectively, may include signaling information in accordance with air interface standards of applicable wireless systems. In this regard, the user computing entity 110 may be capable of operating with one or more air interface standards, communication protocols, modulation types, and access types. More particularly, the user computing entity 110 may operate in accordance with any of a number of wireless communication standards and protocols, such as those described above with regard to the assessment computing entity 100. In a particular embodiment, the user computing entity 110 may operate in accordance with multiple wireless communication standards and protocols, such as UMTS, CDMA2000, 1xRTT, WCDMA, TD-SCDMA, LTE, E-UTRAN, EVDO, HSPA, HSDPA, Wi-Fi, Wi-Fi Direct, WiMAX, UWB, IR, NFC, Bluetooth, USB, and/or the like. Similarly, the user computing entity 110 may operate in accordance with multiple wired communication standards and protocols, such as those described above with regard to the assessment computing entity 100 via a network interface 320.

**[0034]** Via these communication standards and protocols, the user computing entity 110 can communicate with various other entities using concepts such as Unstructured Supplementary Service Data (USSD), Short Message Service (SMS), Multimedia Messaging Service (MMS), Dual-Tone Multi-Frequency Signaling (DTMF), and/or Subscriber Identity Module Dialer (SIM dialer). The user computing entity 110 can also download changes, add-ons, and updates, for instance, to its firmware, software (e.g., including executable instructions, applications, program modules), and operating system.

**[0035]** According to one embodiment, the user computing entity 110 may include location determining aspects, devices, modules, functionalities, and/or similar words used herein interchangeably. For example, the user computing entity 110 may include outdoor positioning aspects, such as a location module adapted to acquire, for example, latitude, longitude, altitude, geocode, course, direction, heading, speed, universal time (UTC), date, and/or various other information/data. In one embodiment, the location module can acquire data, sometimes known as ephemeris data, by identifying the number of satellites in view and the relative positions of those satellites. The satellites may be a variety of different satellites, including Low Earth Orbit (LEO) satellite systems, Department of Defense (DOD) satellite systems, the European Union Galileo

positioning systems, the Chinese Compass navigation systems, Indian Regional Navigational satellite systems, and/or the like. Alternatively, the location information can be determined by triangulating the user computing entity's 110 position in connection with a variety of other systems, including cellular towers, Wi-Fi access points, and/or the like. Similarly, the user computing entity 110 may include indoor positioning aspects, such as a location module adapted to acquire, for example, latitude, longitude, altitude, geocode, course, direction, heading, speed, time, date, and/or various other information/data. Some of the indoor systems may use various position or location technologies including RFID tags, indoor beacons or transmitters, Wi-Fi access points, cellular towers, nearby computing devices (e.g., smartphones, laptops) and/or the like. For instance, such technologies may include the iBeacons, Gimbal proximity beacons, Bluetooth Low Energy (BLE) transmitters, NFC transmitters, and/or the like. These indoor positioning aspects can be used in a variety of settings to determine the location of someone or something to within inches or centimeters.

**[0036]** The user computing entity 110 may also comprise a user interface (that can include a display 316 coupled to a processing element 308) and/or a user input interface (coupled to a processing element 308). For example, the user interface may be a user application, browser, user interface, and/or similar words used herein interchangeably executing on and/or accessible via the user computing entity 110 to interact with and/or cause display of information from the assessment computing entity 100, as described herein. The user input interface can comprise any of a number of devices or interfaces allowing the user computing entity 110 to receive data, such as a keypad 318 (hard or soft), a touch display, voice/speech or motion interfaces, or other input device. In embodiments including a keypad 318, the keypad 318 can include (or cause display of) the conventional numeric (0-9) and related keys (#, \*), and other keys used for operating the user computing entity 110 and may include a full set of alphabetic keys or set of keys that may be activated to provide a full set of alphanumeric keys. In addition to providing input, the user input interface can be used, for example, to activate or deactivate certain functions, such as screen savers and/or sleep modes.

**[0037]** The user computing entity 110 can also include volatile storage or memory 322 and/or non-volatile storage or memory 324, which can be embedded and/or may be removable. For example, the non-volatile memory may be ROM, PROM, EPROM, EEPROM, flash memory, MMCs, SD memory cards, Memory Sticks, CBRAM, PRAM, FeRAM, NVRAM,

MRAM, RRAM, SONOS, FJG RAM, Millipede memory, racetrack memory, and/or the like. The volatile memory may be RAM, DRAM, SRAM, FPM DRAM, EDO DRAM, SDRAM, DDR SDRAM, DDR2 SDRAM, DDR3 SDRAM, RDRAM, TTRAM, T-RAM, Z-RAM, RIMM, DIMM, SIMM, VRAM, cache memory, register memory, and/or the like. The volatile and non-volatile storage or memory can store databases, database instances, database management systems, data, applications, programs, program modules, scripts, source code, object code, byte code, compiled code, interpreted code, machine code, executable instructions, and/or the like to implement the functions of the user computing entity 110. As indicated, this may include a user application that is resident on the entity or accessible through a browser or other user interface for communicating with the assessment computing entity 100 and/or various other computing entities.

**[0038]** In another embodiment, the user computing entity 110 may include one or more components or functionality that are the same or similar to those of the assessment computing entity 100, as described in greater detail above. As will be recognized, these architectures and descriptions are provided for exemplary purposes only and are not limiting to the various embodiments.

### 3. Exemplary Imaging Machine

**[0039]** In various embodiments, an imaging machine 115 may be an imaging machine configured to capture and/or generate imaging information/data used to create a 2D, 3D, or 4D image of a portion of an individual's (e.g., patient, study participant, and/or the like) body. In various embodiments, the imaging machine 115 is configured for capturing and/or generating imaging information/data through at least one of the various imaging techniques and/or processes such as, for example, fluoroscopy, magnetic resonance imaging (MRI), photoacoustic imaging, positron emission tomography (PET), projection radiography, computed axial tomography (CT scan), and ultrasound. In an example embodiment, the imaging machine 115 is an MRI machine configured for capturing and/or generating image information/data of an individual's (e.g., patient, study participant, and/or the like) brain. In an example embodiment, the imaging

machine 115 is an MRI machine configured for diffusion MRI (dMRI), functional MRI (fMRI) imaging, and/or T1 MRI imaging.

**[0040]** In an example embodiment, the imaging machine 115 may be operated by the assessment computing entity 100 and/or other controller computing entity. In an example embodiment, the imaging machine and/or controller computing entity thereof may communicate with the assessment computing entity 100 directly and/or via one or more wired and/or wireless networks 105. For example, the imaging machine 115 may be configured to provide imaging information/data to the assessment computing entity 100 for analysis, storage, and/or the like.

### **III. Exemplary System Operation**

**[0041]** According to various embodiments, the assessment computing entity 100 may be configured to analyze one or more instances of imaging information/data and/or information extracted and/or determined therefrom. In an example embodiment, an instance of imaging information/data may comprise the imaging information/data of one imaging session, and/or a portion of one imaging session, for one individual (e.g., patient, study participant, and/or the like). The term “image” is used generically to refer to a variety of images that can be generated from various imaging techniques and processes. The imaging techniques and processes may include, for instance, fluoroscopy, magnetic resonance imaging (MRI), photoacoustic imaging, positron emission tomography (PET), projection radiography, computed axial tomography (CT scan), and ultrasound. As indicated, the images can be of a human body or one or more parts of the human body (e.g., a patient and/or study participant’s brain), but the images can also be of other organisms or objects. A “volume of images” or “volume” refers to a sequence of images that can be spatially related and assembled into a rectilinear block representing a dimensional region of an individual’s (e.g., patient, study participant, and/or the like) anatomy. Although the following is described in the context of MRI scans, embodiments of the present invention are not limited to this context.

**[0042]** In an example embodiment, one or more instances of imaging information/data may be captured and/or generated for an individual (e.g., patient, study participant, and/or the like), wherein an instance of imaging information/data may comprise a dMRI image and/or a T1 MRI image. For example, dMRI and/or T1 MRI imaging information/data may be analyzed using a bi-tensor analysis to determine the amount and/or fraction of free-water present within one or

more areas of an individual's (e.g., patient, study participant, and/or the like) brain. In an example embodiment, two or more instances of imaging data/information, and/or the analysis thereof, corresponding to the same individual (e.g., patient, study participant, and/or the like) may be compared, analyzed as a set, and/or the like.

**[0043]** In various embodiments, information regarding the free-water fraction and/or  $FA_T$  for multiple parts of the individual's brain is determined based on and/or extracted from the imaging information/data. An individual feature vector is generated based on the information regarding the free-water fraction and/or  $FA_T$  for multiple parts of the individual's brain. The individual feature vector is processed by a machine learning-trained dementia identification and prediction model. In various embodiments, the dementia identification and prediction model is a support vector machine (SVM), a decision tree-based trained model, a naïve Bayes classifier, a neural network-based classifier, a k-nearest neighbors classifier, a feed forward neural network model, a multi-layer perceptron model, a convolutional neural network model, a recurrent neural network model, a long short-term memory network model, a gated recurrent unit model, a radial basis function network model, a capsule network model, a residual neural network model, deep learning model, and/or the like. The dementia identification and prediction model processes the individual feature vector and provides an output identifying a type of dementia and/or rate of progression being experienced by the individual. The output of the dementia identification and prediction model is processed and a type of dementia and/or rate of progression being experienced by the individual is provided via at least one of a graphical representation thereof via a display, an audible representation thereof via a speaker, an automated update of an electronic health record corresponding to the individual, an electronic message (e.g., text message, SMS message, email, push notification, and/or the like), and/or other output means. In various embodiments, a healthcare provider may use the type of dementia and/or rate of progression being experienced by the individual, which was determined by the dementia identification and prediction model, to provide feedback to the individual, determine a care plan and/or treatment plane for the individual, and/or the like.

**[0044]** The type of dementia and/or rate of progression being experienced by an individual (and/or a determination of whether the individual is experiencing dementia) may impact decisions regarding a treatment and/or care plan for an individual. For example, a doctor may describe different medication and/or treatments for an individual experiencing Alzheimer's

dementia compared to an individual experiencing dementia with Lewy bodies. Moreover, for determining the effectiveness of various medications and/or treatments in clinical trials, knowledge of what types of dementia trial participants are experiencing may enable researchers to more efficiently identify medications and/or treatments that are effective for various types of dementia.

**[0045]** Conventionally a type of dementia and/or rate of progression being experienced by an individual is determined by clinical assessment, and based on blood test results, spinal fluid test results, and/or PET ligand scan results. However, these methods are expensive using radiotracers injected into the blood stream, can provide inconclusive results, are not accessible to many lower-income and rural communities, and may require multiple tests taking a full workday from the patient. Therefore, technical and logistical problems exist regarding how to determine a type of dementia and/or rate of progression being experienced by an individual.

**[0046]** Various embodiments of the present disclosure provide technical solutions to these technical problems. For example, non-invasive MRI imaging information/data is used to determine input for a machine learning-trained dementia identification and prediction model. The dementia identification and prediction model provides output indicating a type of dementia and/or rate of progression being experienced by the individual. An example embodiment is able to determine and/or identify a type of dementia and/or rate of progression being experienced by an individual with 80 to 100% accuracy. Therefore, various embodiments provide an effective, non-invasive determination of the type of dementia and/or rate of progression being experienced by an individual.

**[0047]** Moreover, various embodiments include the performance of prediction-based actions based on the type of dementia and/or rate of progression being experienced by an individual. As a non-limiting example, operation of a user computing entity associated with the individual or a caregiver of the individual may be automatically modified and/or tailored based on the type of dementia and/or rate of progression being experienced by the individual. For example, use of a user computing entity associated with the individual to perform tracking of the individual's location and/or movement, provision of reminders (e.g., regarding taking of medication, medical appointments, social engagements, etc.), and/or the like may be automatically enabled and/or modified based at least in part on the prediction of the type of dementia and/or rate of

progression being experienced by the individual. Various embodiments therefore provide technical improvements to technical fields.

**[0048]** Figure 4 provides a flowchart illustrating various processes, procedures, and/or the like for training a machine learning-trained dementia identification and prediction model and using the dementia identification and prediction model to determine and provide a type of dementia and/or rate of progression being experienced by an individual. Starting at step 402, an assessment computing entity 100 obtains training data. In various embodiments, the assessment computing entity 100 comprises means, such as processing element 205, memory 210, 215, communications interface 220, and/or the like, for obtaining training data. In various embodiments, the processing element 205 accesses and/or reads the training data from a database, for example, stored in memory 210, 215. In various embodiments, the assessment computing entity 100 receives the training data via communications interface 220 (e.g., from a database stored by another assessment computing entity 100 and/or the like). In an example embodiment, the assessment computing entity 100 receives imaging data/information from one or more imaging machines 115 and determines and/or generates at least a portion of the training data based thereon. In an example embodiment, the assessment computing entity 100 receives at least a portion of the training data via user input (e.g., via a user input/output device of the assessment computing entity 100 and/or a user computing entity 110 in electronic communication with the assessment computing entity 100).

**[0049]** In various embodiments, the training data includes labelled feature vectors. For example, a labelled feature vector includes an array indicating the free-water fraction (FW) and/or  $FA_T$  for multiple parts of an individual's brain as determined based on imaging information/data of the individual's brain. The labelled feature vector also includes a label (e.g., flag, metadata, and/or array member) indicating a type of dementia and/or rate of progression that the individual is experiencing (e.g., cognitively normal (no dementia), Alzheimer's dementia, dementia with Lewy bodies, frontotemporal dementia, and/or the like).

**[0050]** At step 404, the assessment computing entity 100 trains the dementia identification and prediction model using at least a first portion of the training data. For example, the assessment computing entity 100 comprises means, such as processing element 205, memory 210, 215, and/or the like to train the dementia identification and prediction model using at least a first portion of the training data. In various embodiments, the dementia identification and

prediction model is one of an SVM, a decision tree based trained model, a naïve Bayes classifier, a neural network-based classifier, a k-nearest neighbors classifier, a feed forward neural network model, a multi-layer perceptron model, a convolutional neural network model, a recurrent neural network model, a long short-term memory network model, a gated recurrent unit model, a radial basis function network model, a capsule network model, a residual neural network model, deep learning model, and/or the like. Training the dementia identification and prediction model includes using an appropriate machine learning algorithm for the particular type of model being used.

**[0051]** For example, in some embodiments, the machine learning-trained dementia identification and prediction model is an SVM and training the SVM includes configuring and/or training the SVM to perform a transformation of a feature vector into a class or a probability that a feature vector is a member of one or more classes. For example, via the training, the SVM may learn one or more hyperplanes that distinguishably segregate feature vectors corresponding to different classes. The dementia identification and prediction model may be trained to identify and/or determine one or more hyperplanes that distinguishably segregate and/or separate different classes with the maximum margin. For example, the dementia identification and prediction model may include an input layer configured to receive a feature vector, one or more hidden layers that are trained to transform the feature vector received via the input layer by determining a “location” of a point in a multi-dimensional space corresponding to the feature vector and/or determining a relative location of the point in the multi-dimensional space corresponding to the feature vector with respect to the one or more hyperplanes that are learned and/or defined via the machine learning training procedure of the dementia identification and prediction model, and an output layer that is configured and/or trained to convert the location or relative location information determined via the one or more hidden layers into output information. For example, the output information may be or indicate a class to which the feature vector is expected to correspond to, a likelihood or probability that that feature vector corresponds to one or more classes, and/or the like. In various embodiments, the assessment computing entity 100 is configured to use a machine learning protocol to train the dementia identification and prediction model. For example, in various embodiments, an iterative loss-gradient machine learning process may be used to learn and/or define the one or more

hyperplanes in the multi-dimensional space that distinguishably segregate two or more classes (as represented by the first portion of the training data) with a maximum margin.

**[0052]** At step 406, the assessment computing entity 100 may use a second portion of the training data not used to train the dementia identification and prediction model to test the dementia identification and prediction model. For example, the assessment computing entity 100 comprises means, such as processing element 205, memory 210, 215, and/or the like for using a second portion of the training data to test the dementia identification and prediction model. For example, the second portion of the training data not used to train the dementia identification and prediction model may be processed using the dementia identification and prediction model and the respective outputs of dementia identification and prediction model may be compared to the respective labels associated with the instances of training data of the second portion of the training data not used to train the dementia identification and prediction model to determine an accuracy with which the dementia identification and prediction model is able to identify the type of dementia and/or rate of progression being experienced by an individual.

**[0053]** In an instance where the accuracy with which the dementia identification and prediction model is able to identify the type of dementia and/or rate of progression being experienced by an individual is not suitable for the application, further training may be performed, possibly with the use of additional training data.

**[0054]** Once the dementia identification and prediction model is trained, the dementia identification and prediction model may be used to determine and/or identify the type of dementia and/or rate of progression being experienced by an individual. At step 412, the assessment computing entity 100 obtains information regarding the FW and/or FA<sub>T</sub> for multiple parts of the individual's brain. The information regarding the FW and/or FA<sub>T</sub> for multiple parts of the individual's brain is determined and/or extracted from imaging information/data of the individual's brain.

**[0055]** In various embodiments, the assessment computing entity 100 comprises means, such as processing element 205, memory 210, 215, communications interface 220, and/or the like, for obtaining information regarding the FW and/or FA<sub>T</sub> for multiple parts of the individual's brain. In various embodiments, the processing element 205 accesses and/or reads the information regarding the FW and/or FA<sub>T</sub> for multiple parts of the individual's brain from a database, for example, stored in memory 210, 215. In various embodiments, the assessment computing entity

100 receives the information regarding the FW and/or FA<sub>T</sub> for multiple parts of the individual's brain via communications interface 220 (e.g., from a database stored by another assessment computing entity 100 and/or the like). In an example embodiment, the assessment computing entity 100 receives imaging data/information from one or more imaging machines 115 and determines and/or generates at least a portion of the information regarding the FW and/or FA<sub>T</sub> for multiple parts of the individual's brain based thereon. In an example embodiment, the assessment computing entity 100 receives at least a portion of the information regarding the FW and/or FA<sub>T</sub> for multiple parts of the individual's brain via user input (e.g., via a user input/output device of the assessment computing entity 100 and/or a user computing entity 110 in electronic communication with the assessment computing entity 100).

**[0056]** Figure 5 provides a flowchart of various processes, procedures, operations, and/or the like that may be completed to determine information regarding the FW and/or FA<sub>T</sub> for multiple parts of the individual's brain. The processes, procedures, operations, and/or the like illustrated in Figure 5 are performed by an assessment computing entity 100. In various embodiments, the individual may be an individual patient. In various embodiments, the individual may be a study participant for a drug/treatment study or other treatment study.

**[0057]** Starting at step 502, the assessment computing entity 100 obtains imaging information/data. For example, the assessment computing entity 100 comprises means, such as processing element 205, memory 210, 215, communications interface 220, and/or the like for obtaining imaging information/data. For example, the assessment computing entity 100 may assess the imaging information/data from memory 210, 215, receive the imaging information/data from another computing entity and/or an imaging machine 115. For example, the assessment computing entity 100 may receive from or cause an imaging machine 115 to capture imaging information/data of an individual's brain.

**[0058]** For example, an imaging technician may provide the individual with instructions and position the individual within and/or in the proximity of the imaging machine 115. The imaging technician may then provide input (e.g., via a user input device) to the assessment computing entity 100 to trigger the assessment computing entity 100 to cause, instruct, trigger, and/or the like the imaging machine 115 to capture imaging information/data of the individual. The assessment computing entity 100 may receive the captured imaging information/data from the imaging machine 115 and store the imaging information/data and corresponding metadata in

memory 210, 215. For example, the metadata may include the individual's name or an individual identifier, a date and/or time stamp, information/data identifying the imaging machine 115, and/or the like. In an example embodiment, the imaging information/data captured may comprise dMRI data, T1 MRI data, and/or the like. In various embodiments, the imaging information/data may comprise one or more images of an individual's brain and/or a portion thereof.

**[0059]** At step 504, one or more portions of imaging information/data corresponding to one or more areas of the individual's brain are identified. For example, the one or more areas of the brain that are identified may be referred to as regions of interest. In an example embodiment, the regions of interest may comprise one or more of the corpus callosum, white matter tracts connecting the occipital cortex, white matter tracks connecting the temporal lobe and parietal and frontal lobes, subcortical gray matter regions such as the substantia nigra, globus pallidus, caudate, putamen, subthalamic nucleus, cerebellar regions such as the middle cerebellar peduncle, superior cerebellar peduncle, cerebellar lobule VI, inferior vermis, brainstem regions including the pedunculopontine nucleus, pons, and also key regions of the amygdala, hippocampus, and/or the like. For example, the assessment computing entity 100 may receive user input (e.g., via an input device) that identify portions of imaging information/data corresponding to regions of interest. For example, the assessment computing entity 100 may display one or more images corresponding to the imaging information/data to a skilled technician via an output device (e.g., display of the assessment computing entity 100, display 316 of a user computing entity 110, and/or the like). The assessment computing entity 100 may then receive an indication of user input (e.g., received via an input device of the assessment computing entity 100 or of the user computing entity 110) identifying one or more portions of the one or more images that correspond to particular areas of the individual's brain. For example, the skilled technician may provide input to the input device of the assessment computing entity 100 or user computing entity 110 identifying various areas of the individual's brain.

**[0060]** In an example embodiment, the portions of imaging information/data corresponding to the regions of interest are identified by the assessment computing entity 100. For example, the assessment computing entity 100 may use a trained neural network, deep net, or other model that was trained using machine learning to identify one or more portions of the imaging information/data corresponding to one or more areas of the brain. For example, the assessment computing entity 100 may use a normalization pipeline, one or more templates, and/or the like

for identifying one or more portions of the imaging information/data corresponding to one or more areas of the brain such as the regions of interest.

**[0061]** In various embodiments, the imaging information/data may be pre-processed before being provided (e.g., displayed) for skilled technician identification of the regions of interest and/or automated identification of the regions of interest. For example, in an example embodiment, the imaging information/data may be preprocessed using custom programming scripts and image processing libraries, such as FMRIB Software Library (FSL), AFNI (Analysis of Functional NeuroImages, [afni.nimh.nih.gov](http://afni.nimh.nih.gov)), and/or the like. For example, each scan of the imaging information/data was corrected for signal distortions due to eddy currents and head motion. For example, gradient directions may be rotated in response to the eddy current corrections, and portions of the imaging information/data corresponding to non-brain tissue may be removed from the imaging information/data. In example embodiment, we use custom algorithms to quantify  $b_0$  and corrected fractional anisotropy images from the imaging information/data. In various embodiments, the  $b_0$  image is the diffusion image without gradients applied with diffusion weighting and is similar to a standard T2 weighted MRI. Free-water images and free-water-corrected diffusion tensor images may be calculated using custom algorithms in a computer programming language, MATLAB, R, or another mathematical analysis software based on the imaging information/data. In an example embodiment, a bi-tensor model is used to calculate the signal attenuation as the sum of attenuations arising from two compartments: one that models free-water and a tissue compartment. The free-water-corrected tensor images were also used to calculate free-water corrected fractional anisotropy maps ( $FA_T$ ). Data preprocessing may be used to generate fractional anisotropy,  $b_0$ , free-water,  $FA_T$  and/or other images from and/or based on the imaging data, in various embodiments. In an example embodiment, the fractional anisotropy and  $b_0$  images were multiplied together to maximize contrast in the midbrain and the cortex and will hereafter be referred to as the  $FA*b_0$  image. In an example embodiment, the portions of imaging information/data corresponding to the regions of interest are identified in the  $b_0$  image in subject space. For example, an image provided for skilled technician identification of one or more regions of interest may be a  $b_0$  image in subject space.

**[0062]** In various embodiments, an assessment computing entity 100 is configured to execute and/or operate a normalization pipeline for processing imaging information/data and/or

identifying one or more portions of imaging information/data corresponding to regions of interest. For example, in some example embodiments, ANFI, FLIRT/FNIRT in FSL software, rigid alignment and Symmetric Normalization (SyN) in Advanced Normalization Tools (ANTs) software, and/or other software tool may be used to provide a normalization pipeline for processing imaging information/data and/or identifying one or more portions of imaging information/data corresponding to regions of interest. For example, in some example embodiments, ANFI, FLIRT/FNIRT in FSL software, rigid alignment and Symmetric Normalization (SyN) in Advanced Normalization Tools (ANTs) software, and/or other software tool may be used to generate one or more templates used to identify one or more portions of the imaging information/data corresponding to one or more regions of interest and/or use one or more templates to identify portions of the imaging information/data corresponding to regions of interest. In an example embodiment, at least one of the templates corresponds to and/or is generated based on mean  $b_0$ , fractional anisotropy, or  $b_0 \cdot FA$  images. In an example embodiment, the imaging information/data is analyzed and/or the templates are in Montreal Neurological Institute (MNI) space. Processing through this pipeline is an automated computer driven procedure that can then link to cloud-based architecture or laptops computing devices, or the like (e.g., a user computing entity 110).

**[0063]** In various embodiments, to transform the subject space imaging data (e.g., the imaging information/data received from the imaging machine 115 and/or the pre-processed imaging data) to MNI space, a series of nonlinear and linear registrations may be used. In various embodiments, prior to nonlinear registration, a linear registration (e.g., FLIRT in FSL, a rigid transformation in ANTs, and/or the like) may be applied to the imaging information/data. In an example embodiment, three linear registrations may be completed in FSL, ANTs, and/or the like to get subject-space images to MNI space. In an example embodiment, the three linear registrations comprise (1)  $b_0$  registration to a mean 100 Human Connectome Project (HCP)  $b_0$  template, (2) fractional anisotropy registration to a mean HCP fractional anisotropy template, and (3)  $FA \cdot b_0$  registration to a mean HCP  $FA \cdot b_0$  template. Linear registrations were followed with nonlinear warping (e.g., FNIRT in FSL, SyN in ANTs, and/or the like). In an example embodiment, three different nonlinear warps may be performed for FSL, ANTs, and/or the like. For example, the three different nonlinear warps may comprise (1)  $b_0$  warping to a mean HCP  $b_0$  template, (2) fractional anisotropy warping to a mean HCP fractional anisotropy template, and

(3) FA\*b0 warping to a mean HCP FA\*b0 template. In an example embodiment, default settings may be used for all registration and warping.

**[0064]** At step 506, the assessment computing entity 100 determines and/or extracts information regarding the FW and/or FA<sub>T</sub> for multiple parts of the individual's brain from the imaging information/data. For example, a FW is determined for one or more areas of the brain based on the imaging information/data. For example, the FW for one or more regions of interest may be determined based on the portions of imaging information/data corresponding to the respective regions of interest. For example, the assessment computing entity 100 may determine the FW for a region of interest based on the portion of the imaging information/data identified as corresponding to the region of interest. In various embodiments, the FW is derived from imaging information/data captured via dMRI scan and/or T1 MRI scan. Various methods for deriving the FW for a region of interest may be used in various embodiments. Similarly, the FA<sub>T</sub> for multiple parts of the individual's brain from the imaging information/data.

**[0065]** Returning to Figure 4, at step 414, the assessment computing entity 100 generates an individual feature vector based on the information regarding the FW and/or FA<sub>T</sub> for multiple parts of the individual's brain. For example, the assessment computing entity 100 comprises means, such as processing element 205, memory 210, 215, and/or the like for generating the individual feature vector based on the information regarding the FW and/or FA<sub>T</sub> for multiple parts of the individual's brain. In various embodiments, the individual feature vector is generated based on and/or in accordance with a defined data model. For example, in an example embodiment, the individual feature vector is an array of FW and/or FA<sub>T</sub> for multiple parts of the individual's brain. For example, the defined data model may indicate which position of the array is populated with the FW and/or FA value corresponding to a region of interest of the individual's brain. In an example embodiment, the individual feature vector includes and/or is associated with metadata and/or demographic data, such as the individual's age, geographical region of residence, race, ethnicity, sex, and/or other pertinent information. For example, the dementia identification and prediction model may be trained to perform the classification and/or dementia type and progression rate identification differently for different demographic groups

(e.g., individuals of different ages, geographical regions of residence, race, ethnicity, sex, and/or the like).

**[0066]** At step 416, the assessment computing entity 100 processes the individual feature vector using the dementia identification and prediction model. For example, the assessment computing entity 100 comprises means, such as processing element 205, memory 210, 215, and/or the like, for processing the individual feature vector using the dementia identification and prediction model. For example, the individual feature vector may be provided as input to the dementia identification and prediction model. The dementia identification and prediction model may then process the individual feature vector to determine and/or identify a type of dementia and/or rate of progression corresponding to the individual feature vector.

**[0067]** For example, in an example embodiment, the dementia identification and prediction model includes an SVM, and the dementia identification and prediction model determines which region of a hypervolume corresponding to the defined data model of the individual feature vector the individual feature vector corresponds to and/or is disposed within. The dementia identification and prediction model then determines the type of dementia and/or rate of progression associated with the region of the hypervolume within which the individual feature vector corresponds to and/or is disposed within. In various embodiments, the divisions between the regions of the hypervolume are determined as part of the machine learning process performed at step 404.

**[0068]** For example, the dementia identification and prediction model may include an input layer configured to receive the individual feature vector. The input layer may pass the feature vector to one or more hidden layers of the dementia identification and prediction model that are trained to transform the feature vector received via the input layer by determining a “location” of a point in a multi-dimensional space corresponding to the feature vector and/or determining a relative location of the point in the multi-dimensional space corresponding to the feature vector with respect to the one or more hyperplanes that were learned and/or defined via the machine learning training procedure of the dementia identification and prediction model. The dementia identification and prediction model further includes an output layer that is configured and/or trained to convert the location or relative location information determined via the one or more hidden layers into output information. For example, the output information may indicate a class to which the feature vector is expected to correspond to, a likelihood or probability that that

feature vector corresponds to one or more classes, and/or the like. For example, the output information may indicate a type of dementia and/or rate of progression corresponding to the individual feature vector. The dementia identification and prediction model provides the determined and/or identified type of dementia and/or rate of progression corresponding to the individual feature vector as output.

**[0069]** For example, the assessment computing entity 100 may provide the individual feature vector to the dementia identification and prediction model via an application programming interface (API) call, calling the dementia identification and prediction model via a function call, and/or the like. The dementia identification and prediction model may then be executed to determine output information that indicates a type of dementia and/or rate of progression corresponding to the individual feature vector. The dementia identification and prediction model returns the output information indicating a type of dementia and/or rate of progression corresponding to the individual feature vector via an API call, function response/output, and/or the like.

**[0070]** At step 418, the assessment computing entity 100 processes the output of the dementia identification and prediction model to determine a type of dementia and/or rate of progression being experienced by the individual. For example, the assessment computing entity 100 comprises means, such as processing element 205, memory 210, 215, and/or the like for processing the output of the dementia identification and prediction model to determine a type of dementia and/or rate of progression being experienced by the individual. For example, the dementia identification and prediction model provides an indication of a type of dementia and/or rate of progression corresponding to the individual feature vector via an API call, function response/output, and/or the like. The assessment computing entity 100 processes the indication of a type of dementia and/or rate of progression corresponding to the individual feature vector to determine a type of dementia and/or rate of progression being experienced by the individual.

**[0071]** At step 420, the assessment computing entity 100 provides the type of dementia and/or rate of progression being experienced by the individual (and/or an indication thereof). For example, the assessment computing entity 100 comprises means, such as processing element 205, memory 210, 215, communications interface 220, and/or the like, for providing the type of dementia and/or rate of progression being experienced by the individual (and/or an indication thereof). For example, the assessment computing entity 100 may cause the user computing entity

110 to display a graphical representation of the type of dementia and/or rate of progression being experienced by the individual (e.g., for viewing by a technician and/or healthcare provider) via display 316. For example, the assessment computing entity 100 may cause the user computing entity 110 to provide an audible representation of the type of dementia and/or rate of progression being experienced by the individual via a speaker of the user computing entity 100 (e.g., for a technician and/or healthcare provider to hear). In an example embodiment, the assessment computing entity 100 may cause an electronic health record corresponding to the individual to be updated to include the type of dementia and/or rate of progression being experienced by the individual. For example, the assessment computing entity 100 may provide and/or transmit an electronic message for receipt by a healthcare records maintenance system to cause the healthcare records maintenance system to update the electronic health record corresponding to the individual to be updated to include the type of dementia and/or rate of progression being experienced by the individual. For example, the assessment computing entity 100 may transmit an electronic message (e.g., text message, SMS message, email, push notification, and/or the like) including the type of dementia and/or rate of progression being experienced by the individual. The electronic message may be configured to provide information regarding the type of dementia and/or rate of progression being experienced by the individual to a technician and/or healthcare provider.

**[0072]** A healthcare provider may use the type of dementia and/or rate of progression being experienced by the individual to determine a treatment plan for the individual, categorize the individual for a drug/treatment trial, and/or the like.

**[0073]** For example, in various embodiments, one or more prediction-based actions may be taken and/or performed responsive to the output information and/or the type of dementia and/or rate of progression being experienced by the individual. Such prediction-based actions may include automated alerts; automated instructions to medical devices; automated adjustments to medical equipment; automated adjustments to allocations of medical, computing, hospital, facility, and/or human resources; automated adjustments to tracking of the individual's location and/or activities; automated adjustments to notifications and/or reminders provided to the individual (e.g., via a user computing entity associated with the individual such as the individual's television, mobile phone, smartphone, tablet, and/or the like); and/or the like.

[0074] For example, some forms of dementia include symptoms related to loss of memory. When the information regarding the type of dementia and/or rate of progression being experienced by the individual is form of dementia including symptoms related to loss of memory, one or more geofences may be automatically defined such that when the individual (as tracked via tracking of a user computing entity associated with the individual) exits one of the geofences, an automated alert is provided to a caregiver. In another example, some forms of dementia include symptoms related to impaired motor skills. When the information regarding the type of dementia and/or rate of progression being experienced by the individual is form of dementia including symptoms related to impaired motor skills, one or more fall alerts may be activated such that when the individual (as tracked via tracking of a user computing entity associated with the individual) does not change location within a set time period, a user computing entity may request interaction from the individual (e.g., indicating whether the individual is ok or needs assistance) and an automated alert may be provided to a caregiver based on the individual's response to the interaction request. Various other medication and/or appointment reminders may be automatically scheduled and/or provided (e.g., via a user computing entity associated with the individual or a caregiver of the individual) based at least in part on the type of dementia and/or rate of progression being experienced by the individual.

[0075] Further, such automated actions may include automated physician notification actions, automated patient notification actions, automated appointment scheduling actions, automated prescription recommendation actions, automated drug prescription generation actions, automated implementation of precautionary actions, automated record updating actions, automated datastore updating actions, automated hospital preparation actions, automated workforce management operational management actions, automated server load balancing actions, automated resource allocation actions, automated call center preparation actions, automated hospital preparation actions, automated pricing actions, automated plan update actions, automated alert generation actions, generating a diagnostic report, generating action scripts, generating one or more electronic communications, and/or the like. The one or more prediction-based actions may further include displaying visual renderings of the aforementioned examples of prediction-based actions in addition to values, charts, and representations associated with the one or more policy scores and the prediction output using a prediction output user interface.

[0076] As discussed herein, some techniques of the present disclosure enable the generation of new machine learning models with parameters specifically trained and tailored to perform one or more predictive actions to achieve real-world effects. The machine learning models of the present disclosure may be used, applied, and/or otherwise leveraged to generate predictions of a type of dementia and/or rate of progression experienced by an individual. These predictions may be leveraged to initiate the performance of various computing tasks that improve the performance of a computing system (e.g., a computer itself, etc.) with respect to various predictive actions performed by the computing system. For example, the prediction of the type of dementia and/or rate of progression being experienced by the individual may be used to tailor operation of a user computing entity associated with the individual (e.g., tracking functions, reminders, etc.) based on the type of dementia and/or rate of progression being experienced by the individual.

#### **IV. Conclusion**

[0077] Many modifications and other embodiments of the inventions set forth herein will come to mind to one skilled in the art to which these inventions pertain having the benefit of the teachings presented in the foregoing descriptions and the associated drawings. Therefore, it is to be understood that the inventions are not to be limited to the specific embodiments disclosed and that modifications and other embodiments are intended to be included within the scope of the appended claims. Although specific terms are employed herein, they are used in a generic and descriptive sense only and not for purposes of limitation

## CLAIMS

1. A computer-implemented method for determining at least one of a type of dementia or a rate of progression being experienced by an individual, the method comprising:

obtaining, by one or more processors, information regarding at least one of free-water fraction or free-water corrected fractional anisotropy (FA<sub>T</sub>) for multiple parts of an individual's brain;

generating, by the one or more processors, an individual feature vector based on the information regarding at least one of free-water fraction or free-water corrected fractional anisotropy (FA<sub>T</sub>) for multiple parts of the individual's brain;

processing, by the one or more processors, the individual feature vector using a machine learning-trained dementia identification and prediction model to obtain a model output indicating at least one of a type of dementia or a rate of progression being experienced by the individual; and

providing, by the one or more processors, output indicating at least one of the type of dementia or the rate of progression being experienced by the individual.

2. The method of claim 1, wherein the information regarding at least one of free-water fraction or free-water corrected fractional anisotropy (FA<sub>T</sub>) for multiple parts of the individual's brain is extracted or determined based on magnetic resonance imaging (MRI) data of the individual's brain.

3. The method of claim 2, further comprising:

obtaining MRI data of the individual's brain; and

processing the MRI data of the individual's brain to extract or determine the information regarding at least one of free-water fraction or free-water corrected fractional anisotropy (FA<sub>T</sub>) for multiple parts of an individual's brain.

4. The method of claim 1, wherein the dementia identification and prediction model is a support vector machine (SVM).

5. The method of claim 1, wherein the dementia identification and prediction model is configured to provide the model output indicating one of: cognitively normal, Alzheimer's dementia, dementia with Lewy bodies, or frontotemporal dementia.
6. The method of claim 1, wherein the individual feature vector includes both information regarding free-water fraction for multiple parts of the individual's brain and information regarding  $FA_T$  for multiple parts of the individual's brain.
7. The method of claim 1, wherein providing the output indicating at least one of the type of dementia or the rate of progression being experienced by the individual comprises at least one of:
  - causing display of the output via a display;
  - causing the output to be audibly provided;
  - updating an electronic health record corresponding to the individual with the output; or
  - transmitting an electronic message including the output.
8. An apparatus comprising at least one processor and a memory storing computer executable instructions, the memory and the computer executable instructions configured to, when executed by the at least one processor, cause the apparatus to perform at least:
  - obtaining information regarding at least one of free-water fraction or free-water corrected fractional anisotropy ( $FA_T$ ) for multiple parts of an individual's brain;
  - generating an individual feature vector based on the information regarding at least one of free-water fraction or free-water corrected fractional anisotropy ( $FA_T$ ) for multiple parts of the individual's brain;
  - processing the individual feature vector using a machine learning-trained dementia identification and prediction model to obtain a model output indicating at least one of a type of dementia or a rate of progression being experienced by the individual; and
  - providing output indicating at least one of the type of dementia or a rate of progression being experienced by the individual.
9. The apparatus of claim 8, wherein the information regarding at least one of free-water fraction or free-water corrected fractional anisotropy ( $FA_T$ ) for multiple parts of the individual's

brain is extracted or determined based on magnetic resonance imaging (MRI) data of the individual's brain.

10. The apparatus of claim 9, wherein the memory and computer executable instructions are further configured to, when executed by the at least one processor, cause the apparatus to perform at least:

obtaining MRI data of the individual's brain; and

processing the MRI data of the individual's brain to extract or determine the information regarding at least one of free-water fraction or free-water corrected fractional anisotropy (FA<sub>T</sub>) for multiple parts of an individual's brain.

11. The apparatus of claim 8, wherein the dementia identification and prediction model is a support vector machine (SVM).

12. The apparatus of claim 8, wherein the dementia identification and prediction model is configured to provide the model output indicating one of: cognitively normal, Alzheimer's dementia, dementia with Lewy bodies, or frontotemporal dementia.

13. The apparatus of claim 8, wherein the individual feature vector includes both information regarding free-water fraction for multiple parts of the individual's brain and information regarding FA<sub>T</sub> for multiple parts of the individual's brain.

14. The apparatus of claim 8, wherein providing the output indicating at least one of the type of dementia or a rate of progression being experienced by the individual comprises at least one of:

causing display of the output via a display;

causing the output to be audibly provided;

updating an electronic health record corresponding to the individual with the output; or

transmitting an electronic message including the output.

15. A computer program product comprising at least one non-transitory computer readable storage medium storing computer executable instructions, the computer executable instructions configured, when executed by at least one processor of an apparatus, cause the apparatus to perform:

obtaining information regarding at least one of free-water fraction or free-water corrected fractional anisotropy ( $FA_T$ ) for multiple parts of an individual's brain;

generating an individual feature vector based on the information regarding at least one of free-water fraction or free-water corrected fractional anisotropy ( $FA_T$ ) for multiple parts of the individual's brain;

processing the individual feature vector using a machine learning-trained dementia identification and prediction model to obtain a model output indicating at least one of a type of dementia or a rate of progression being experienced by the individual; and

providing output indicating at least one of the type of dementia or a rate of progression being experienced by the individual.

16. The computer program product of claim 15, wherein the information regarding at least one of free-water fraction or free-water corrected fractional anisotropy ( $FA_T$ ) for multiple parts of the individual's brain is extracted or determined based on magnetic resonance imaging (MRI) data of the individual's brain.

17. The computer program product of claim 16, wherein the computer executable instructions are further configured, when executed by the at least one processor of the apparatus, cause the apparatus to perform:

obtaining MRI data of the individual's brain; and

processing the MRI data of the individual's brain to extract or determine the information regarding at least one of free-water fraction or free-water corrected fractional anisotropy ( $FA_T$ ) for multiple parts of an individual's brain.

18. The computer program product of claim 15, wherein the dementia identification and prediction model is a support vector machine (SVM).

19. The computer program product of claim 15, wherein the dementia identification and prediction model is configured to provide the model output indicating one of: cognitively normal, Alzheimer's dementia, dementia with Lewy bodies, or frontotemporal dementia.
20. The computer program product of claim 15, wherein providing the output indicating at least one of the type of dementia or a rate of progression being experienced by the individual comprises at least one of:
- causing display of the output via a display;
  - causing the output to be audibly provided;
  - updating an electronic health record corresponding to the individual with the output; or
  - transmitting an electronic message including the output.