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(54) Title: METHOD AND SYSTEM FOR PREDICTING NAFLD STAGES BY PROCESSING MEDICAL IMAGES

(57) Abstract: The present disclosure discloses a method and system for processing medical images for predicting a Non-Alcoholic Fatty Liver Disease (NAFLD) stage (213). The method comprises receiving the medical image (305) from one or more data sources (203) and identifying an image type of the medical image (305) from an among plurality of image types. Further, the method comprises pre-processing the medical image (305) using a respective pre-processing pipeline selected from a plurality of pre-processing pipelines (401) based on the image type of the medical image (305). Thereafter, the method comprises processing the pre-processed medical image (307) using a trained deep learning model for generating a classification probability score (309) associated with the medical image (305). Finally, the method comprises predicting the NAFLD stage (213), from the medical image among a plurality of NAFLD stages based on the generated classification score (309).

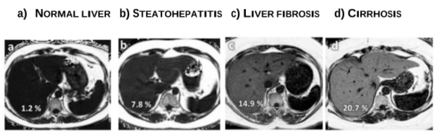

Figure 1A

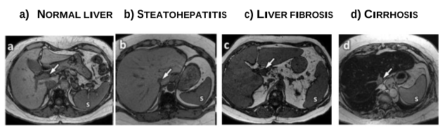

Figure 1B

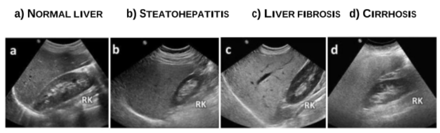

Figure 1C

<u>FORM 2</u>

THE PATENTS ACT 1970
(39 OF 1970)
&
The Patent Rules, 2003

Complete Specification

(See Section 10 and Rule 13)

1. TITLE OF THE INVENTION

METHOD AND SYSTEM FOR PREDICTING NAFLD STAGES BY PROCESSING MEDICAL IMAGES

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3. PREAMBLE TO THE DESCRIPTION

COMPLETE

The following specification describes the invention and the manner in which it is to be performed

TECHNICAL FIELD

[001] The present disclosure generally relates to identifying liver fibrosis and classifying a liver fibrosis stage in a non-invasive manner using Artificial Intelligence (AI). More particularly, the present disclosure relates to a method and system for predicting stages of Non-Alcoholic Fatty Liver Disease (NAFLD) by processing medical images.

BACKGROUND

[002] Non-Alcoholic Fatty Liver Disease (NAFLD) is a type of liver disease where fat is deposited in the liver due to non-alcohol related reasons. In other words, the NAFLD refers to abnormal fat accumulation in liver. Generally, the NAFLD is identified in an overweight person or obese people. The NAFLD is a major cause for liver dysfunction and is highly prevalent. The progression of NAFLD involves four stages. For example, a Normal liver stage, a Steatohepatitis (fatty liver) stage, a Liver fibrosis stage, and a Cirrhosis stage. The normal liver stage is a condition of the liver where the liver is normal and there is no accumulated excessive fat (i.e., fat accumulation is below a threshold limit). The Steatohepatitis (fatty liver) stage is a condition of the liver where the accumulation of fat is within a pre-defined range (which is typically more than the normal stage and less than the liver fibrosis stage). The liver fibrosis stage is a condition of the liver where the accumulation of the fat in the liver is within another pre-defined range (which is typically more than the Steatohepatitis stage and less than the cirrhosis stage). The cirrhosis is the stage of the liver where the fat accumulation is beyond a threshold limit.

[003] In the Steatohepatitis stage, the deposits of fat may cause liver enlargement. In the liver fibrosis stage, there may be a formation of scar tissues and subsequently, may cause damage to liver cells. Finally, in the Cirrhosis stage, due to the scar tissue the liver may become hard and may be unable to function properly. Hence, it is necessary to identify the NAFLD stages and classify the NAFLD stages as normal stage, Steatohepatitis stage, liver fibrosis stage, or Cirrhosis stage.

[004] Conventionally, the NAFLD stages within a subject are identified by capturing at least one medical image of the subject using any image device (e.g., a Computed Tomography (CT) image, a Magnetic Resonance Image (MRI) image, and an ultrasound image) and then analysing the captured medical images to find out the stage of NAFLD from among the normal, Steatohepatitis, liver fibrosis or Cirrhosis. For instance, **Figure 1A** shows the NAFLD stages (i.e., normal stage, Steatohepatitis stage, liver fibrosis stage, or Cirrhosis stage) in a Computed

Tomography (CT) image. **Figure 1B** shows the NAFLD stages in a Magnetic Resonance Image (MRI) image, and **Figure 1C** shows the NAFLD stages in an ultrasound image.

[005] In conventional techniques, the NAFLD stages may be identified and classified individually for different types of the medical images. That is, if the NAFLD stages should be identified and classified using a CT image, then a separate end-to-end setup/model (typically a machine learning based model) is required which can pre-process the CT images only and subsequently identifying the NAFLD stages. Similarly, if the NAFLD stage should be identified and classified using an MRI image, a separate end-to-end model is required (i.e., different from the model used for CT images) which can pre-process and classify the MRI images only. Finally, if the NAFLD stage should be identified and classified using an ultrasound images, then a separate model is required (i.e., different from the models used for the CT images and the MRI images) which can pre-process and classify only the ultrasound images.

[006] Since, the conventional techniques require different end-to-end models for pre-processing the different types of medical images, the process of identifying the NAFLD stages and classifying the NAFLD stages individually for different images may be inefficient, time consuming, costly, and may not even provide accurate identification and/or classification results. For instance, in the conventional techniques, requiring different end-to-end models for pre-processing and then classifying different medical image would need more resources (such as processing power, computing/processing resources, storage, etc.) for training and deployment of different models which would also consume more time. Moreover, in such models, typically a user has to manually provide medical image to a corresponding model depending on type of the image and any mismatch in providing the medical image would result in inaccurate and unreliable results in identification and classification of the NAFLD stages. Hence, there is a need for techniques which can pre-process different medical images using a single end-to-end model in a time and resource efficient manner to accurately classify the NAFLD stages.

[007] The information disclosed in this background of the disclosure section is only for enhancement of understanding of the general background of the invention and should not be taken as an acknowledgement or any form of suggestion that this information forms the prior art already known to a person skilled in the art.

SUMMARY

[008] In an embodiment, the present disclosure discloses a method of processing medical images for predicting a Non-Alcoholic Fatty Liver Disease (NAFLD) stage. The method comprises receiving the medical image from one or more data sources and identifying an image type of the medical image from an among plurality of image types. Further, the method comprises pre-processing the medical image using a respective pre-processing pipeline selected from a plurality of pre-processing pipelines based on the image type of the medical image. Thereafter, the method comprises processing the pre-processed medical image using a trained deep learning model for generating a classification probability score associated with the medical image. Finally, the method comprises predicting the NAFLD stage, from the medical image among a plurality of NAFLD stages based on the generated classification score.

[009] In an embodiment, the present disclosure discloses a system for processing medical images to predict a Non-Alcoholic Fatty Liver Disease (NAFLD) stage from a medical image. The system comprises a processor and a memory. The processor is configured to receive the medical image from one or more data sources. Further, the processor is configured to identify an image type of the medical image from among a plurality of image types. Furthermore, the processor is configured to pre-process the medical image using a respective pre-processing pipeline selected from a plurality of pre-processing pipelines based on the image type of the medical image. Thereafter, the processor is configured to process the pre-processed medical image using a trained deep learning model for generating a classification probability score. Finally, the processor is configured to predict the NAFLD stage, from the medical image, among a plurality of NAFLD stages based on the generated classification probability score.

[0010] The foregoing summary is illustrative only and is not intended to be in any way limiting. In addition to the illustrative aspects, embodiments, and features described above, further aspects, embodiments, and features will become apparent by reference to the drawings and the following detailed description.

BRIEF DESCRIPTION OF THE ACCOMPANYING DRAWINGS

[0011] The novel features and characteristics of the disclosure are set forth in the appended claims. The disclosure itself, however, as well as a preferred mode of use, further objectives, and advantages thereof, will best be understood by reference to the following detailed description of an illustrative embodiment when read in conjunction with the accompanying figures. One or more embodiments are now described, by way of example only, with reference to the accompanying figures wherein like reference numerals represent like elements and in which:

[0012] Figures 1A-1C illustrate various NAFLD stages of liver for different types of medical images.

[0013] Figure 2 illustrates an exemplary environment **200** showing a prediction system **201** for processing medical images for predicting a Non-Alcoholic Fatty Liver Disease (NAFLD) stage from a medical image, in accordance with some embodiments of the present disclosure.

[0014] Figure 3 illustrates a detailed block diagram **300** of the prediction system **201** shown in **Figure 2**, in accordance with some embodiments of the present disclosure.

[0015] Figure 4 illustrates a high-level block diagram **400** showing a plurality of pre-processing pipelines for preprocessing different types of medical images, in accordance with some embodiments of the present disclosure.

[0016] Figure 5A shows an exemplary illustration **500-1** with various output images during pre-processing of a CT image using a CT image pre-processing pipeline, in accordance with some embodiments of the present disclosure.

[0017] Figure 5B shows an exemplary illustration **500-2** with various output images during pre-processing of an MRI image using an MRI image pre-processing pipeline, in accordance with some embodiments of the present disclosure.

[0018] Figure 5C shows an exemplary illustration **500-3** with various output images during pre-processing of an ultrasound image using an ultrasound image pre-processing pipeline, in accordance with some embodiments of the present disclosure.

[0019] Figure 6A shows an architecture **600a** of a deep learning model (for e.g., a CNN) for predicting NAFLD stages from given medical images, in accordance with some embodiments of the present disclosure.

[0020] Figure 6B shows a detailed block diagram **600b** for training a deep learning model, in accordance with some embodiments of the present disclosure.

[0021] **Figure 7** shows a flowchart illustrating an exemplary method **700** for processing medical images for predicting a NAFLD stage from a medical image, in accordance with some embodiments of the present disclosure.

[0022] It should be appreciated by those skilled in the art that any block diagram herein represents conceptual views of illustrative systems embodying the principles of the present subject matter. Similarly, it will be appreciated that any flow charts, flow diagrams, state transition diagrams, pseudo code, and the like represent various processes which may be represented in computer readable medium and executed by a computer or processor, whether or not such computer or processor is explicitly shown.

DETAILED DESCRIPTION

[0023] In the present document, the word "exemplary" is used herein to mean "serving as an example, instance, or illustration." Any embodiment or implementation of the present subject matter described herein as "exemplary" is not necessarily to be construed as preferred or advantageous over other embodiments.

[0024] While the disclosure is susceptible to various modifications and alternative forms, specific embodiment thereof has been shown by way of example in the drawings and will be described in detail below. It should be understood, however that it is not intended to limit the disclosure to the particular forms disclosed, but on the contrary, the disclosure is to cover all modifications, equivalents, and alternatives falling within the scope of the disclosure.

[0025] The terms “comprises”, “comprising”, or any other variations thereof, are intended to cover a non-exclusive inclusion, such that a setup, device, or method that comprises a list of components or steps does not include only those components or steps but may include other components or steps not expressly listed or inherent to such setup or device or method. In other words, one or more elements in a system or apparatus proceeded by “comprises… a” does not, without more constraints, preclude the existence of other elements or additional elements in the system or apparatus.

[0026] The present disclosure overcome some or all of the above-mentioned problems by providing a single end-to-end model which comprises different pre-processing pipelines for automatically pre-processing different medical images and a single AI based model for accurately classifying the NAFLD stages for all types of medical images in a time and resource efficient manner.

[0027] Particularly, the present disclosure proposes a single pre-processing module that accepts different types of medical images (e.g., CT images, MRI images, or ultrasound image of NAFLD) and followed by different pre-processing pipelines corresponding to the different types of images. Specifically, a given medical image may be loaded onto different data loaders. The data loaders may automatically identify type of the medical image and load the medical image to respective pre-processing pipeline. The pre-processed image may be passed to a trained deep learning model. The deep learning model may extract features from the pre-processed image and may generate a classification probability score. The classification probability score may indicate a class to which the pre-processed image (i.e., the input medical image) belongs to and based on the generated classification score, the corresponding NAFLD stage may be identified.

[0028] Figure 2 illustrates an exemplary environment **200** showing a prediction system **201** for processing medical images and subsequently predicting Non-Alcoholic Fatty Liver Disease (NAFLD) stages from the medical images, in accordance with some embodiments of the present disclosure.

[0029] As illustrated in **Figure 2**, the exemplary environment **200** may comprise a prediction system **201** communicatively connected via a communication network **205** with one or more data sources **203**. In an embodiment, the prediction system **201** may be any computing system which may be configured for predicting a NAFLD stage from a medical image by processing the received medical image. The medical image may provide functional and anatomical information (i.e., the medical image may be an image that display visual representation of function of some organs or tissues). For example, the medical image may be a 2D image or a 3D image dataset of an object obtained from a Computed Tomography (CT) scanner, a Magnetic Resonance Imaging (MRI) scanner, an ultrasound scanner, X-ray scanner, etc. to guide medical interventions for research purposes.

[0030] The prediction system 2**01** may include one or more processors **211**, a memory **209**, and an Input/Output (I/O) interface **207**. In some embodiments, the memory **209** may be communicatively coupled to the one or more processors **211**. The one or more processors **211** may comprise at least one data processor for executing program components for executing user or system-generated requests. The memory **209** may store instructions, executable by the one or more processors **211**, which on execution, may cause the one or more processors **211** to predict the NAFLD stage **213** from a medical image. The I/O interface **207** may be coupled with the one or more processors **211** through which an input signal and/or an output signal may be communicated. For example, the medical image may be received from one or more data sources **203** via the I/O interface **207**. In an embodiment, the prediction system **201** may be implemented in a variety of computing systems, such as, but not limited to, a tablet, a server, a network server, a cloud-based server, and the like.

[0031] The one or more data sources **203** may provide the medical image to the prediction system **201** (e.g., via the network **205**). The one or more data sources **203** may include, without limitation, image capturing units (e.g., CT scanners, MRI scanners, ultrasound scanners, X-ray scanners, etc.), a cloud database, an internal databases, and the like. The communication network **205** may include, without limitation, a direct interconnection, a peer to peer (P2P) network, a Local Area Network (LAN), a Wide Area Network (WAN), a wireless network (for example, using Wireless Application Protocol), an internet, Wi-Fi, and the like.

[0032] In an embodiment, the prediction system **201** may receive a medical image of a subject from the one or more data sources **203** through the communication network **205**. After receiving the medical image, the prediction system **201** may automatically identify an image type of the medical image from among a plurality of image types. In one embodiment, the prediction system **201** may determine modality information and/or a Voxel Hounsfield Unit (HU) associated with the medical image. The modality information of the medical image (specifically for Digital Imaging and Communication in Medicine (DICOM) image) may be a tag present on the medical image which displays the type of the medical image. The nature of acquisition results in a quantitative measurement of tissue density relative to water is known as Hounsfield unit. The Voxel HU values in the medical images may be largely considered as reproducible with slight differences across different scanners and pressure specifications. The Voxel HU values may be dependent on image intensity values of the CT image, the MRI image, and the ultrasound image.

[0033] Based on the modality information and/or the Voxel HU values, the predication system **201** may identify the image type of the medical images among a plurality of image types. The plurality of image types may include, without limitation, the CT image, the MRI image, the ultrasound image, and the like. The modality information of the medical image may facilitate the process of categorizing the medical image into the CT image, the MRI image, or the ultrasound image. The Voxel HU may be a relative quantitative measurement of radio density used by radiologists in an interpretation of the CT image, the MRI image, and the ultrasound image. The Voxel HU may be calculated using the below equation or formula. i.e.,

$$HU = \left(\frac{\mu_{material} - \mu_{water}}{\mu_{water}}\right) \times 1000$$

Where 'μ' is a linear attenuation coefficient for the respective medical image. The Voxel HU values may be different for different elements. Typical values for different element and tissues may range from -1000 to more than +1000, air versus bone. In another embodiment, the prediction system **201** may make use of the data (medical image) loaders to identify the image type of the medical image and to load the medical image into the respective pre-processing pipeline.

[0034] After identifying the type of the medical image, the prediction system **201** may pre-process the medical image using a respective pre-processing pipeline based on the image type of the medical image. As an example, the prediction system **201** may comprise a plurality of pre-processing pipelines (not shown in **Figure 1**) to pre-process the medical image. The plurality of pre-processing pipelines may include, without limitation, a CT image pre-processing pipeline, a MRI image pre-processing pipeline, an ultrasound image pre-processing pipeline.

[0035] If the received medical image is identified as the CT image (based on modality information or its Voxel HU value), then the received medical image (i.e., the CT image) may be passed into the CT image pre-processing pipeline, and subsequently, the CT image pre-processing pipeline may produce a pre-processed medical image (i.e., the pre-processed CT image). Similarly, if the received medical image is identified as the MRI image (based on modality information or its Voxel HU value), then the received medical image (i.e., the MRI image) may be passed into the MRI image pre-processing pipeline, and subsequently, the MRI image pre-processing pipeline may produce a pre-processed medical image (i.e., the pre-processed MRI image). Likewise, if the received medical image is identified as the ultrasound image (based on modality information or its Voxel HU value), then the received medical image (i.e., the ultrasound image) may be passed into the ultrasound image pre-processing pipeline, and subsequently, the ultrasound image pre-processing pipeline may produce a pre-processed medical image (i.e., the pre-processed ultrasound image).

[0036] After pre-processing the medical image using a respective pre-processing pipeline and obtaining the pre-processed medical image, the prediction system **201** may process the pre-processed medical image using a trained deep learning model for generating a classification probability score associated with the medical image. The trained deep learning model may detect and classify texture properties of the pre-processed medical image. The deep learning model may be made up of convolutional layers, max-pooling layers, and fully connected layers or dense layers along with an activation function in hidden layers and a softmax function which may be employed in the fully connected layers. Dropouts may be used in the deep learning model to reduce an effect of over-fitting. As an example, the deep learning model may include, but not limited to, at least one of a Convolution Neural Network (CNN), a Recurrent Neural Network (RNN), a Long Short-term Memory (LSTM), a recursive neural network, a graph convolutional network, a sequential neural network, a combination thereof, and the like. A person skilled in the art will appreciate that the present disclosure is applicable to any artificial intelligence or neural network other than the above-mentioned neural networks.

[0037] The trained deep learning model may extract features from the pre-processed image of the subject and generate a classification probability score. The classification probability score may indicate a class to which the pre-processed image belongs to and based on the generated classification score, the prediction system **201** may predict corresponding NAFLD stage. Specifically, the deep learning model may extract the features from the pre-processed medical image and may generate convolved feature maps (which may be smaller in size). The convolved features maps may be used to obtain discriminative feature representation. Due to the small size of each of the convolutional feature map, maximum local information of the texture may be captured. In order to extract critical features, for example, edges a stride, and a length of a pad may be set to one pixel. The above mentioned features and textures are extracted and learned by the deep learning model followed by tuning itself based on the loss which is generated at every epoch. Accordingly, the classification probability score may be generated based on the above process which indicates probable class of the input image or medical image **305**.

[0038] **Figure 3** illustrates a detailed block diagram **300** of the prediction system **201** shown in **Figure 2**, in accordance with some embodiments of the present disclosure. As shown in

Figures 1-2, the prediction system **201** may comprise the interface(s) **207**, the memory **209**, and the processor(s) **211**.

[0039] In an embodiment, the memory **209** may include various types of data **301**. In one implementation, the data **301** may include, for example, one or more medical images **305**, one or more pre-processed medical images **307**, classification scores **309** The prediction system **201** may further comprise one or more modules or means or units **303**. In one implementation, the modules **303** may include, for example, a receiving module **313**, an identification module **315**, a pre-processing module **317**, a processing module **319**, a prediction module **321**, and other modules **323.** In an embodiment, each of the one or more modules **303** may be a hardware unit which may be outside the memory **209** and coupled with the prediction system **201**. In such embodiment, each module may refer to an Application Specific Integrated Circuit (ASIC), an electronic circuit, a Field-Programmable Gate Arrays (FPGA), Programmable System-on-Chip (PSoC), a combinational logic circuit, and/or other suitable components that provide described functionality. The one or more modules **303** when configured with the described functionality defined in the present disclosure may result in a novel hardware. In another implementation, each of the one or more modules **303** may be software modules which may reside within the memory **209**.

[0040] In an embodiment, the medical image **305** may be a 2D image or a 3D image datasets of a subject obtained from an medical image scanner to guide medical interventions for research purposes. The medical image **305** may be received from the one or more data sources **203**.

[0041] In an embodiment, the pre-processed medical images **307** may be images which are pre-processed using the respective pre-processing pipelines among the plurality of pre-processing pipelines. The pre-processed medical images **307** may include one of the pre-processed CT images, the pre-processed MRI images, and the pre-processed ultrasound images, but not limited thereto. In an embodiment, the classification scores **309** may comprise one or more pre-defined classification score ranges indicating fat accumulation corresponding for various NAFLD stages. For example, depending on the fat accumulation, the NAFLD may be classified into a normal stage/class (or normal liver), a grade/class 1 stage (or Steatohepatitis stage), a grade/class 2 stage (or Liver Fibrosis stage), a grade/class 3 stage (or Cirrhosis stage). Specifically, if the fat accumulation within the liver is less than 5%, the NAFLD may be classified as normal stage. fat accumulation. The grade 1 stage of the NAFLD may indicate more than 5% of fat accumulation and less than 33% of the fat accumulation. The grade 2 stage of the NAFLD may indicate more than 33% of fat accumulation and less than 66% of the fat accumulation. The grade 3 stage of the NAFLD may indicate more than 66% of the fat accumulation. The other data **311** may include temporary data and temporary files generated by the one or more modules **303** for performing the various functions of the prediction system **201**.

[0042] In an embodiment, the receiving module **313** may be configured to receive the medical image of a subject from the one or more data sources **203**. The identification module **315** may be configured to identify an image type of the received medical image from among a plurality of image types. The plurality of image types may include at least one of the CT image, the MRI image, and the ultrasound image. In an embodiment, the pre-processing module **317** may be configured to pre-process the medical image using a respective pre-processing pipeline selected from a plurality of pre-processing pipelines based on the image type of the medical image. The pre-processing module **317** may include a CT pre-processing pipeline, a MRI pre-processing pipeline, and an ultrasound pre-processing pipeline, as shown in **Figure 4**.

[0043] In an embodiment, the processing module **319** may be configured to process the pre-processed medical image **307** using a trained deep learning model for generating a probability score **309** associated with the medical image. In an embodiment, the prediction module **321** may be configured to predict the NAFLD stage **213**, from the medical image **305**, among a plurality of NAFLD stages based on comparison of the generated classification probability score with the classification scores **309**.

[0044] In an embodiment, the one or more modules **303** may also include the other modules **323** to perform various miscellaneous functionalities of the prediction system **201**. It will be appreciated that the one or more modules **303** may be represented as a single module or a combination of different modules.

[0045] **Figure 4** illustrates a block diagram **400** showing a plurality of pre-processing pipelines **401** for pre-processing different types of medical images. In an embodiment, the plurality of pre-processing pipelines **401** may be a part of the pre-processing module **317** and may comprise a CT image pre-processing pipeline **403**, an MRI image pre-processing pipeline **405**, and an ultrasound image pre-processing pipeline **407**.

[0046] Each of the plurality of pre-processing pipelines **401** may comprise one or more modules. For instance, the CT image pre-processing pipeline **403** may include, without limitation, a denoising module **409,** an interpolation module **411**, an image registration module (optional not shown in the **Figure 4**), an image normalization module **413**, a zero padding module **415**, and the like. The MRI image pre-processing pipeline **405** may include, without limitation, a denoising module **417**, a bias field correction module **419**, an image standardization module **421**, and the like. The ultrasound image pre-processing pipeline **407** may include, without limitation, a noise filtering module **423**, a contrast enhancement module **425**, a resolution enhancement module **427**, and the like.

[0047] The medical image **305** may be received from the one or more data sources **203**. If the received medical image **305** is identified as the CT image, then the CT image is pre-processed using the CT image pre-processing pipeline **403**, as shown in **Figure 5A**. **Figure 5A** shows an exemplary illustration **500-1** with various output images during pre-processing of a CT image using the CT image pre-processing pipeline **403**, in accordance with some embodiments of the present disclosure.

[0048] If the received medical image **305** is identified as the MRI image, then the MRI image is pre-processed using the MRI pre-processing pipeline **405**, as shown in **Figure. 5B**. **Figure 5B** shows an exemplary illustration **500-2** with various output images during pre-processing of an MRI image using an MRI image pre-processing pipeline **405**, in accordance with some embodiments of the present disclosure. If the received medical image **305** is identified as the ultrasound image, then the ultrasound image may be pre-processed using the ultrasound pre-processing pipeline **407**, as shown in **Figure 5C**. **Figure 5C** shows an exemplary illustration **500-3** with various output images during pre-processing of an ultrasound image using an ultrasound image pre-processing pipeline **407**, in accordance with some embodiments of the present disclosure.

[0049] Now, **Figure 4** is explained in conjunction with **Figures 5A-5C** for pre-processing the different medical images using the different pre-processing pipelines, in accordance with some embodiments of the present disclosure. Referring to **Figure 4** and **Figure 5A**, when the received medical image **305** is identified as the CT image, then the CT image is pre-processed using the CT image pre-processing pipeline **403**. In the CT image pre-processing pipeline **403**, firstly, the received CT medical image is processed using the denoising module **409**. The denoising module **409** may remove noise from the CT image to produce a denoised CT image.

The denoising module **409** may use one or more algorithms to remove the noise from the CT image. For example, the denoising module **409** may use Gaussian blurring algorithm or Dark outliers filter to produce the denoised CT image. The present disclosure is not limited thereto. For denoising the CT image any suitable algorithms may also be used. The CT image may include noise, edge and texture with high frequency components and it may be difficult to distinguish them in the process of denoising and the images may lose some details or information. Hence, the gaussian blurring algorithm and/or dark outliers filters may be used for denoising the medical image, as shown in **Figure 5A**.

[0050] In the next step, the denoised medical image is passed into the interpolation module **411**. The interpolation module **411** may estimate pixel intensity values of one or more pixels present in the denoised CT image based on one or more neighbouring pixel values to produce an interpolated CT image. The interpolation module **411** may use one or more algorithms to estimate pixel intensity values of one or more pixels in the denoised CT image. For example, the interpolation module **411** may use nearest neighbour interpolation algorithm for estimating the pixel intensity values. Specifically, the interpolation module **411** may resize or resample the denoised image to meet the specifications of transmission channel or to provide final image with no loss.

[0051] In the next step, the interpolated image is passed into the image normalization module **413** to produce a normalized CT image. The image normalization module **413** may change a range of pixel intensity values in the interpolated CT image. The image normalization module **413** may use standard methods for the image normalization.

[0052] Finally, in the CT image pre-processing pipeline **401**, the zero padding module **415** may adjust a size of the normalized CT image to produce a pre-processed CT image. The Zero padding may be performed to match the size of the normalized CT image with the original CT image. In the next step, the pre-processed CT image **307** may be passed into the deep learning model.

[0053] Referring to **Figure 4** and **Figure 5B**, when the received medical image **305** is identified as the MRI image, then the MRI image is passed into the MRI image pre-processing pipeline **405**.

[0054] In the MRI image pre-processing pipeline **405**, firstly, the denoising module **417** may receive the MRI medical image. The denoising module **417** may remove noise from the MRI image to produce a denoised MRI image. The denoising module **417** in the MRI pre-processing pipeline **405** may use one or more algorithms to remove the noise from the MRI Image. For example, the denoising module **417** may use Median Blur filter for removing the noise from the received medical image **305** and subsequently, may produce denoised MRI image. The present disclosure is not limited thereto. For denoising the MRI image any suitable algorithms may be used. The MRI images may produce artifacts and blurry images. Hence, to remove the artifacts and blurry part in the MRI image the Median blur filter may be used.

[0055] In the next step, the denoised MRI image is passed into the bias filed correction module 419. The bias field correction module **419** may perform bias field correction on the denoised MRI image to produce a distortion free MRI image. The "bias filed" distortion may be a low-frequency or non-uniformity in the MRI image data. This distortion causes the MRI intensity values to vary across the images obtained from scanner. The bias field correction may be performed using an algorithm. For example, the bias field correction module **419** may use N4 bias field correction algorithm. The present disclosure is not limited thereto.

[0056] Finally, the distortion free image is passed into the image standardization module **421**. The image standardization module **421** may rescale attributes of the distortion free MRI image to produce the pre-processed MRI image. The objective of performing the MRI image standardization is to bring down all the features of the image to a common scale without distorting differences between range of the values. In the next step, the pre-processed MRI image may be passed into the deep learning model.

[0057] Referring to **Figure 4** and **Figure 5C**, when the received medical image **305** is identified as the ultrasound image, then the ultrasound image is passed into the ultrasound image pre-processing pipeline **407**.

[0058] In the ultrasound image pre-processing pipeline **407**, firstly, the noise filtering module **423** may remove noise from the ultrasound image to produce denoised ultrasound image. The noise filtering module **423** may use speckle noise removal algorithm or a Gaussian filter in order to remove the noise from the ultrasound image. The present disclosure is not limited there to. Any suitable algorithms may be used to filter the noise from the ultrasound images.

[0059] In the next step, the denoised ultrasound image may be passed into the contrast enhancement module **425**. The contrast enhancement module **425** may perform contrast enhancement off the denoised ultrasound image. The contrast enhancement module **425** may use a Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm to enhance the contrast of the denoised ultrasound image. The present disclosure is not limited thereto. Any suitable algorithm may be used.

[0060] Finally, the denoised ultrasound image (i.e., contrast enhanced image) may be passed into the resolution enhancement module **427**. The resolution enhancement module **427** may perform resolution enhancement on the denoised ultrasound image to produce pre-processed ultrasound image **307** with an improved quality. The resolution enhancement module **427** may use an algorithm for enhancing the resolution of the ultrasound image. For example, the resolution enhancement module **427** may use Linear contrast adjustment algorithm for enhancing the resolution of the ultrasound image to produce pre-processed ultrasound image.

[0061] After producing the pre-processed medical image, the pre-processed medical image is passed into the deep-learning model. The deep learning model may be a Convolutional Neural Network (CNN). The present disclosure is not limited thereto. After receiving the pre-processed medical image **307**, the deep learning model may extract features from the pre-processed medical image **307** and may generate an output comprising a convolved feature map. The output feature map size may be determined by the size of the input feature map (i.e., pre-processed medical image) during convolution. To convolve the input feature map, kernel filters may be applied to the input feature map, then the output feature map may be reduced in size. In the input image, there may be a loss of information at the borders of the input feature map. To preserve the information padding may be performed.

[0062] After extracting the features from the pre-processed image, the deep learning model may generate a probability score for the received medical image. The generated probability score may indicate a class to which the pre-processed image belongs to. Next, the generated probability score may be compared with the one or more pre-defined classification score ranges and based on the comparison, corresponding NAFLD stage may be identified within the subject.

[0063] Figure 6A shows an architecture **600a** of a deep learning model (for e.g., a CNN) for predicting NAFLD stages from given medical images, in accordance with some embodiments of the present disclosure.

[0064] As shown in **Figure 6A**, a pre-processed medical image **307** may be provided as input to the architecture **600a**. The architecture **600a** may comprise a plurality of sequential layers and the plurality of sequential layers may comprise a plurality of stacks, each stack may comprise one convolutional layer and one max pooling layer. The plurality of stacks may be followed by a plurality of fully connected layers or dense layers.

[0065] The convolutional layer may be a core building block of the architecture **600a**. The convolutional layer may contain parameters of a set of 'K' learnable filters. Each filter may comprise a width and a height. The convolutional layer may receive the input image and may extract features of the received input image and may generate a convolved map or a feature map. The max pooling layer may be present after the convolutional layer in the architecture **600a**. The max pooling layer may receive the convolved map or feature map from the convolutional layer and may reduce size of the convolved map in order to reduce computations. The fully connected layers may be the last layer of the architecture **600a** followed by an output layer (e.g., a softmax layer).

[0066] Referring to **Figure 6A**, the pre-processed medical image **307** (for example, a CT image, a MRI image, or an ultrasound image) may be provided to the convolution layer. The convolution layer may extract the features from the pre-processed medical image **307** and may generate a feature map. The convolution layer may use multiple 'K' learnable filters for extracting the multiple features from the pre-processed medical image **307**. The multiple features may include, without limitation, edges in an image, colour of the image, brightness of the image, and the like. Subsequently, the generated feature map may be passed into the max pooling layer. The max pooling layer may receive the feature map and may down-sample or reduce the dimensions of the received feature map. After reducing the size of the received feature map, the max pooling layer may use filters to generate a pooled feature map.

[0067] In the next step, the feature map from the max pooling layer may be passed to another convolution layer. The other convolution layer may extract the features of the pooled feature map by using suitable filters and generates a feature map. The feature map may be provided to another max pooling layer. The other max pooling layer may adjust the size of the received feature map. The above functions may be repeated for number of times to obtain pooled feature map.

[0068] In the next step, flattening may be performed on the obtained pooled feature map. Specifically, the pooled feature map be a 2D array. The flattening process converts the 2D array into a single continuous linear vector. The single continuous linear vector may be fed into the fully connected layers. The fully connected layers may use SoftMax function. The SoftMax function may be a last activation function of the architecture **600a** to normalize the output of architecture **600a** to a probability distribution over predicted output stages. The predicted output may be compared with the actual output to identify and classify the NAFLD stage **213** in image.

[0069] It may be noted that the deep learning model needs to be trained using a dataset of medical image **305** before implementing or deployment. The training of the deep learning model is explained in forthcoming paragraphs with the help of **Figure 6B** that shows a detailed block diagram **600b** for training the deep learning model, in accordance with some embodiments of the present disclosure**.**

[0070] Initially, the dataset of the medical image **305** is obtained. Each image of the dataset may be pre-processed depending on its image type using respective pipeline in the pre-processing module **317**. Subsequently, the pre-processing module **317** may output pre-processed dataset. The pre-processed dataset may be passed to the deep learning model. The deep learning model may extract features from the pre-processed dataset. Subsequently, the deep learning model may split the extracted features into training dataset and testing dataset.

[0071] In an exemplary aspect, 70-80% of the extracted features are used in a training phase and remaining 20-30% of the extracted features are used in a testing phase such that no features is a part of the both the training and testing phase. The model is trained using the training dataset. Once the first phase of training is complete, the testing dataset is used for testing accuracy of the trained model. In order to identify and/or classify the NAFLD stage **213** in a test medical image, the deep learning model may generate probability score which may be compared with the actual score associated with the test medical image to determine a difference between the generated probability score and the actual score. The difference may indicate the accuracy or correctness of classifier while determining the NAFLD stage **213** in the pre-processed test medical image. For the ideal classifier, the difference between the generated probability score and the actual score should be zero. If the difference is large, it means that the classifier may be unable to correctly identify and classify the stage of the NAFLD in the pre-processed image. Therefore, the difference between the generated probability score and the actual score should be minimum to the possible extent.

[0072] In one non-limiting embodiment of the present disclosure, the deep learning model may be configured to tune one or more hyper parameters or classifier parameters of the classifier so as to minimize the difference between the generated probability score and the actual score. The tuning of one or more hyper parameters may comprise choosing a set of optimal parameters for the classifier which may minimize the difference between the generated probability score and the actual score. In one non-limiting embodiment, the difference between the generated probability score and the actual score may also be known as the degree of error, which may be computed using a loss function such as, but not limited to, cross entropy, mean squared error. The one or more hyper parameters of the classifier may then be updated using techniques such as, but not limited to, gradient descent technique such that the degree of error is minimized. In one non-limiting embodiment, the deep learning model may determine that the one or more hyper parameters are optimal when it is not possible to minimize the difference or the degree of error beyond a limit. For example, when the value of difference remains constant/invariant for a predetermined number of iteration (i.e., the classifier performance stops improving), the deep learning model may determine that the current hyper parameters are optimal parameters for the available dataset of pre-processed medical image.

[0073] The deep learning model may then generate a classifier model whose parameters are set to the determined optimal classifier parameters. The classifier model may be a decent classifier model for identifying and/or classifying the NAFLD stage **213** on the pre-processed medical image

[0074] Figure 7 shows a flowchart illustrating a method **700** for processing medical images for predicting a Non-Alcoholic Fatty Liver Disease (NAFLD) stage from a medical image, in accordance with some embodiments of the present disclosure. As illustrated in **Figure 7**, the method **700** may comprise one or more steps. The method **700** may be described in the general context of computer executable instructions. Generally, computer executable instructions can include routines, programs, objects, components, data structures, procedures, modules, and functions, which perform particular functions or implement particular abstract data types.

[0075] The order in which the method **700** is described is not intended to be construed as a limitation, and any number of the described method blocks can be combined in any order to implement the method. Additionally, individual blocks may be deleted from the methods without departing from the scope of the subject matter described herein. Furthermore, the method can be implemented in any suitable hardware, software, firmware, or combination thereof.

[0076] At block **702**, the method **700** comprises receiving, by a processor **211** associated with a prediction system **201**, the medical image **305** from one or more data source **203**. The medical image **305** may be received from the one or more data sources **203**. At block **704**, the method **700** comprises identifying, by the processor **211**, an image type of the medical image **305** from among a plurality of image types . In an embodiment, the plurality of image types may comprise a CT image, an MRI image, and an ultrasound image. For example, the processor **211** may determine modality information or a Voxel Hounsfield unit value associated with the medical image and identify the image type of the medical image as the CT image, the MRI image, or the ultrasound image based on modality information and their respective Voxel HU unit values.

[0077] At block **706**, the method **700** comprises pre-processing, by the processor **211**, the medical image **305** using a respective pre-processing pipeline selected from a plurality of pre-processing pipelines **401** based on the image type of the medical image **305**. The plurality of pre-processing pipelines **401** may comprise a Computed Tomography (CT) image pre-processing pipeline **403**, a Magnetic Resonance Image (MRI) image pre-processing pipeline **405**, and an ultrasound image pre-processing pipeline **407**. Upon identifying the received medical image **305** as one of the CT image, the MRI image, or the ultrasound image, the medical image **305** are passed into the respective pre-processing pipeline. For example, if the medical image **305** is identified as the CT image, then the CT image may be passed into the CT image pre-processing pipeline **403**. The CT image pre-processing pipeline **403** may perform pre-processing of the CT image. The CT image pre-processing pipeline **403** may remove noise from the CT image to produce a denoised CT image. The CT image pre-processing pipeline **403** may estimate pixel intensity values of one or more pixels present in the denoised CT image based on one or more neighbouring pixel values to produce an interpolated CT image. The CT pre-processing pipeline **403** may change a range of pixel intensity values in the interpolated CT image to produce a normalized CT image. Finally, the

CT image pre-processing pipeline **403** may adjust a size of the normalized CT image to produce a pre-processed CT image **307**.

[0078] Similarly, if the medical image **305** is identified as the MRI image, then the MRI image may be passed into the MRI image pre-processing pipeline **405**. The MRI image pre-processing pipeline **405** may perform pre-processing of the MRI image. Firstly, the MRI pre-processing pipeline **405** may remove noise from the MRI image to produce a denoised MRI image. In the next step, the MRI pre-processing pipeline **405** may perform bias field correction on the denoised MRI Image to produce a distortion free MRI image. Finally, the MRI pre-processing pipeline **405** may rescale attributes of the distortion free MRI image to produce a denoised MRI image.

[0079] Likewise, if the medical image is identified as the ultrasound image, then the ultrasound image may be passed into the ultrasound image pre-processing pipeline **407**. The ultrasound image pre-processing pipeline **407** may perform pre-processing of the ultrasound image. Firstly, the ultrasound pre-processing pipeline **407** may remove noise from the ultrasound image to produce a denoised ultrasound image. In the next step, the ultrasound image pre-processing pipeline **407** may perform contrast enhancement on the denoised ultrasound image and subsequently, perform resolution enhancement on the denoised ultrasound image to produce the pre-processed ultrasound image with improved quality.

[0080] At block **708**, the method comprises processing, by the processor **211**, the pre-processed medical image **307** using a trained deep learning model for generating a classification probability score **309** associated with the medical image **305**. The pre-processed medical image **307** may be passed into the trained deep learning model. For example, a CNN model. The trained deep learning model may generate classification score **309** based on the training features extracted from the pre-processed medical image **307**. At block **710**, the method comprises predicting, by the processor **211**, the NAFLD stage **213**, from the medical image, among a plurality of NAFLD stages on the classification probability score **309**.

Advantages of the present disclosure.

[0081] In the present disclosure, a single end-to-end model is used for pre-processing different types of medical images and accurately classifying the NAFLD stages. As a result, there is no requirement of different end-to-end models for pre-processing different types of medical images and subsequently classifying the NAFLD stages. The techniques of the present disclosure automatically identify a type of a received medical image and automatically pass the received medical image to a corresponding pre-processing pipeline, thereby avoiding manual efforts.

[0082] The present disclosure may require limited resources since the single end-to-end model (having single AI model) is used for pre-processing and classifying the different types of medical images. As a result, minimal resources (such as processing power, computing/processing resources, storage, etc.) are required for training and deployment of the single end-to-end model. Hence, the techniques consistent with the present disclosure automatically and accurately predict NAFLD stages from a medical image of a subject in a time and resource efficient manner.

[0083] Terms "an embodiment", "embodiment", "embodiments", "the embodiment", "the embodiments", "one or more embodiments", "some embodiments", and "one embodiment" mean "one or more (but not all) embodiments of the invention(s)" unless expressly specified otherwise.

[0084] The terms "including", "comprising", “having” and variations thereof mean "including but not limited to", unless expressly specified otherwise.

[0085] The enumerated listing of items does not imply that any or all of the items are mutually exclusive, unless expressly specified otherwise. The terms "a", "an" and "the" mean "one or more", unless expressly specified otherwise.

[0086] A description of an embodiment with several components in communication with each other does not imply that all such components are required. On the contrary a variety of optional components are described to illustrate the wide variety of possible embodiments of the invention.

[0087] When a single device or article is described herein, it will be readily apparent that more than one device/article (whether or not they cooperate) may be used in place of a single device/article. Similarly, where more than one device or article is described herein (whether or not they cooperate), it will be readily apparent that a single device/article may be used in place of the more than one device or article, or a different number of devices/articles may be used instead of the shown number of devices or programs. The functionality and/or the features of a device may be alternatively embodied by one or more other devices which are not explicitly described as having such functionality/features. Thus, other embodiments of the invention need not include the device itself.

[0088] In alternative embodiments, certain operations may be performed in a different order, modified, or removed. Moreover, steps may be added to the above-described logic and still conform to the described embodiments. Further, operations described herein may occur sequentially or certain operations may be processed in parallel. Yet further, operations may be performed by a single processing unit or by distributed processing units.

[0089] Finally, the language used in the specification has been principally selected for readability and instructional purposes, and it may not have been selected to delineate or circumscribe the inventive subject matter. It is therefore intended that the scope of the invention be limited not by this detailed description, but rather by any claims that issue on an application based here on. Accordingly, the disclosure of the embodiments of the invention is intended to be illustrative, but not limiting, of the scope of the invention, which is set forth in the following claims.

[0090] While various aspects and embodiments have been disclosed herein, other aspects and embodiments will be apparent to those skilled in the art. The various aspects and embodiments disclosed herein are for purposes of illustration and are not intended to be limiting, with the true scope being indicated by the following claims.

Referral Numerals:

Referral number	Description
200	Exemplary environment
201	Prediction system
203	One or more data sources
205	Communication network
207	I/O interface
209	Memory
211	Processor
213	NAFLD stage
301	Data
303	Modules

305	Medical image
307	Pre-processed medical image
309	Classification scores
311	Other data
313	Receiving module
315	Identification module
317	Pre-processing module
319	Processing module
321	Prediction module
323	Other modules
401	Plurality of pre-processing pipelines
403	CT image pre-processing pipeline
405	MRI image pre-processing pipeline
407	Ultrasound image pre-processing pipeline
409	Denoising module
411	Interpolation module
413	Image normalization module
415	Zero padding module
417	Denoising module
419	Bias field correction module
421	Standardization module
423	Noise filtering module
425	Contrast enhancement module
427	Resolution enhancement module

WE CLAIM:

1. A method (700) of processing medical images for predicting a Non-Alcoholic Fatty Liver Disease (NAFLD) stage (213) from a medical image (305), the method comprising:

receiving, by a processor (211) associated with the predication system (201), the medical image (305) from one or more data sources (203);

identifying, by the processor (211), an image type of the medical image (305) from among a plurality of image types;

pre-processing, by the processor (211), the medical image (305) using a respective pre-processing pipeline selected from a plurality of pre-processing pipelines (401) based on the image type of the medical image (305);

processing, by the processor (211), the pre-processed medical image (307) using a trained deep learning model for generating a classification probability score (309) associated with the medical image (305); and

predicting, by the processor (211), the NAFLD stage (213), from the medical image (305), among a plurality of NAFLD stages based on the classification probability score (309).

2. The method (700) as claimed in claim 1, wherein identifying an image type of the medical image (305) from among a plurality of image types comprises:

determining modality information or a Voxel Hounsfield unit value associated with the medical image (305); and

identifying the image type of the medical image (305) from a plurality of image types comprising a Computed Tomography (CT) image, a Magnetic Resonance Image (MRI) image, and an ultrasound image based on the modality information or the Voxel Hounsfield unit value.

3. The method (700) as claimed in claim 1, wherein the plurality of pre-processing pipelines (401) comprises a Computed Tomography (CT) image pre-processing pipeline (403), a Magnetic Resonance Image (MRI) image pre-processing pipeline (405), and an ultrasound image pre-processing pipeline (407).

4. The method (700) as claimed in claim 3, wherein the CT pre-processing pipeline (403) comprises a denoising module (409), an interpolation module (411), an image normalization module (413), and a zero padding module (415).

5. The method (700) as claimed in claim 4, wherein when the image type of the medical image (305) is identified as a CT image, pre-processing the medical image (305) comprises performing pre-processing of the CT image using the CT image pre-processing pipeline (403) by:

removing noise from the CT image using the denoising module (409) to produce a denoised CT image;

estimating, using the interpolation module (411), pixel intensity values of one or more pixels present in the denoised CT image based on one or more neighbouring pixel values to produce an interpolated CT image;

changing a range of pixel intensity values in the interpolated CT image using the image normalization module (413) to produce a normalized CT image; and

adjusting a size of the normalized CT image using a zero padding module (415) to produce a pre-processed CT image (307).

6. The method as claimed in claim 3, wherein the MRI pre-processing pipeline (405) comprises a denoising module (417), a bias field correction module (419), and a standardization module (421).

7. The method (700) as claimed in claim 6, wherein when the image type of the medical image (305) is identified as an MRI image, pre-processing the medical image (305) comprises performing pre-processing of the MRI image using the MRI pre-processing pipeline (405) by:

removing noise from the MRI image using the denoising module (417) to produce a denoised MRI image;

performing bias field correction on the denoised MRI image using the bias field correction module (419) to produce a distortion free MRI image;

rescaling attributes of the distortion free MRI image using the image standardization module (421) to produce a pre-processed MRI image (307).

8. The method (700) as claimed in claim 3, wherein the ultrasound image pre-processing pipeline (407) comprises a noise filtering module (423), a contrast enhancement module (425), and a resolution enhancement module (427).

9. The method (700) as claimed in claim 8, wherein when the image type of the medical image (305) is identified as an ultrasound image, pre-processing the medical image comprises

performing the pre-processing of the ultrasound image using the ultrasound pre-processing pipeline (407) by:

removing noise from the ultrasound image using the noise filtering module (423) to produce a denoised ultrasound image;

performing contrast enhancement on the denoised ultrasound image using the contrast enhancement module (425); and

performing resolution enhancement on the denoised ultrasound image using the resolution enhancement module (427) to produce an ultrasound image with improved quality.

10. A prediction system (201) for processing medical images to predict a Non-Alcoholic Fatty Liver Disease (NAFLD) stage (213) from a medical image (305), the prediction system (201) comprising:

a memory (209); and

a processor (211) communicatively coupled to the memory (209) and configured to:

receive the medical image (305) from one or more data sources (203);

identify an image type of the medical image from among a plurality of image types ;

pre-process the medical image (305) using a respective pre-processing pipeline selected from a plurality of pre-processing pipelines (401) based on the image type of the medical image (305);

process the pre-processed medical image (307) using a trained deep learning model for generating a classification probability score (309) associated with the medical image (305); and

predict the NAFLD stage (213), from the medical image (205), among a plurality of NAFLD stages based on the classification probability score (309).

11. The predication system (201) as claimed in claim 10, wherein to identify an image type of the medical image (205) from among a plurality of image types , the processor (211) is configured to

determine modality information or a Voxel Hounsfield unit value associated with the medical image (305); and

identify the image type of the medical image (305) from a plurality of image types comprising a Computed Tomography (CT) image, a Magnetic Resonance (MRI) image, and an ultrasound image based on the modality information or the Voxel Hounsfield unit value.

12. The prediction system (201) as claimed in claim 10, wherein the plurality of pre-processing pipelines (401) comprises a Computed Tomography (CT) image pre-processing pipeline (403), a Magnetic Resonance Image (MRI) image pre-processing pipeline (405), and an ultrasound image pre-processing pipeline (407).

13. The prediction system (201) as claimed in claim 12, wherein the CT pre-processing pipeline (403) comprises a denoising module (409), an interpolation module (411), an image normalization module (413), and a zero padding module (415).

14. The prediction system (201) as claimed in claim 13, wherein when the image type of the medical image (305) is identified as a CT image, the processor (211) is configured to perform pre-processing of the CT image using the CT image pre-processing pipeline (403) by:

removing noise from the CT image using the denoising module (409) to produce a denoised CT image;

estimating, using the interpolation module (411), pixel identity values of one or more pixels present in the denoised CT image based on one or more neighbouring pixel values to produce an interpolated CT image;

changing a range of pixel intensity values in the interpolated CT image using the image normalization module (413) to produce a normalized CT image; and

adjusting a size of the normalized CT image using the zero padding module (415) to produce a pre-processed CT image.

15. The prediction system (201) as claimed in claim 12, wherein the MRI pipeline comprises a denoising module (417), a bias field correction module (419), and a standardization module (421).

16. The predication system (201) as claimed in claim 15, wherein when the image type of the medical image (305) is identified as an MRI image, the processor (211) is configured to perform pre-processing of the MRI image using the MRI image pre-processing pipeline (405) by:

removing noise from the MRI image using the denoising module (417) to produce a denoised MRI image;

performing a bias field correction on the denoised MRI image using the bias field correction module (419) to produce a distortion free MRI image; and rescaling attributes of the distortion free MRI image using the image standardization module (421) to produce a pre-processed MRI image.

17. The predication system (201) as claimed in claim 12, wherein the ultrasound image pre-processing pipeline (407) comprises a noise filtering module (423), a contrast enhancement module (425), and a resolution enhancement module (427).

18. The predication system (201) as claimed in claim 17, wherein when the image type of the medical image (305) is identified as an ultrasound image, the processor (211) is configured to perform pre-processing of the ultrasound image using the ultrasound pre-processing pipeline (407) by:

removing noise from the ultrasound image using the noise filtering module (423) to produce a denoised ultrasound image;

performing contrast enhancement on the denoised ultrasound image using the contrast enhancement module (425); and

performing resolution enhancement on the denoised ultrasound image using the resolution enhancement module (427) to produce an ultrasound image with improved quality.

Dated this 26th day of June 2023

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ABSTRACT

METHOD AND SYSTEM FOR PREDICTING NAFLD STAGES BY PROCESSING MEDICAL IMAGES

The present disclosure discloses a method and system for processing medical images for predicting a Non-Alcoholic Fatty Liver Disease (NAFLD) stage (213). The method comprises receiving the medical image (305) from one or more data sources (203) and identifying an image type of the medical image (305) from an among plurality of image types. Further, the method comprises pre-processing the medical image (305) using a respective pre-processing pipeline selected from a plurality of pre-processing pipelines (401) based on the image type of the medical image (305). Thereafter, the method comprises processing the pre-processed medical image (307) using a trained deep learning model for generating a classification probability score (309) associated with the medical image (305). Finally, the method comprises predicting the NAFLD stage (213), from the medical image among a plurality of NAFLD stages based on the generated classification score (309).

[Figure 2]

a) NORMAL LIVER b) STEATOHEPATITIS c) LIVER FIBROSIS d) CIRRHOSIS

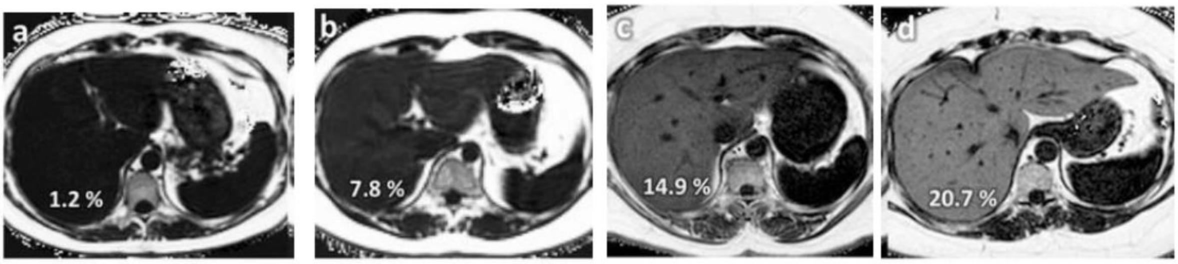

Figure 1A

a) NORMAL LIVER b) STEATOHEPATITIS c) LIVER FIBROSIS d) CIRRHOSIS

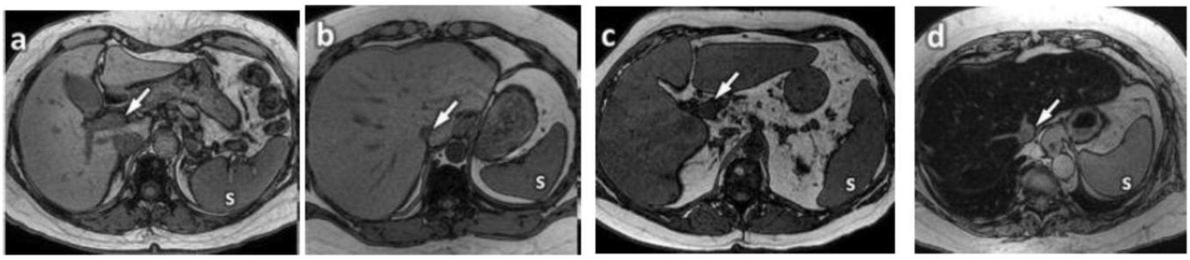

Figure 1B

a) NORMAL LIVER b) STEATOHEPATITIS c) LIVER FIBROSIS d) CIRRHOSIS

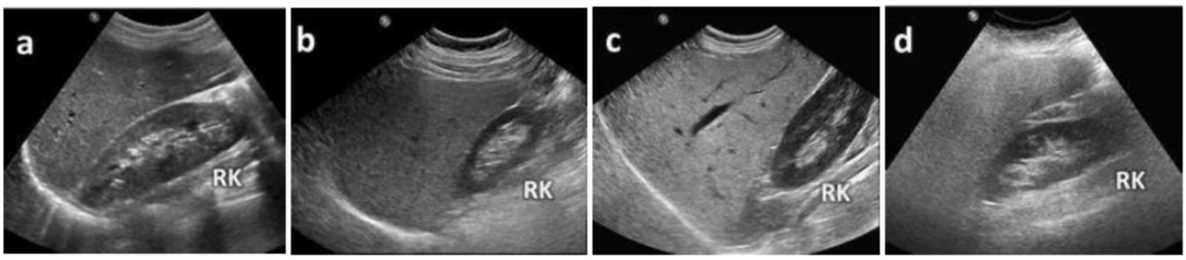

Figure 1C

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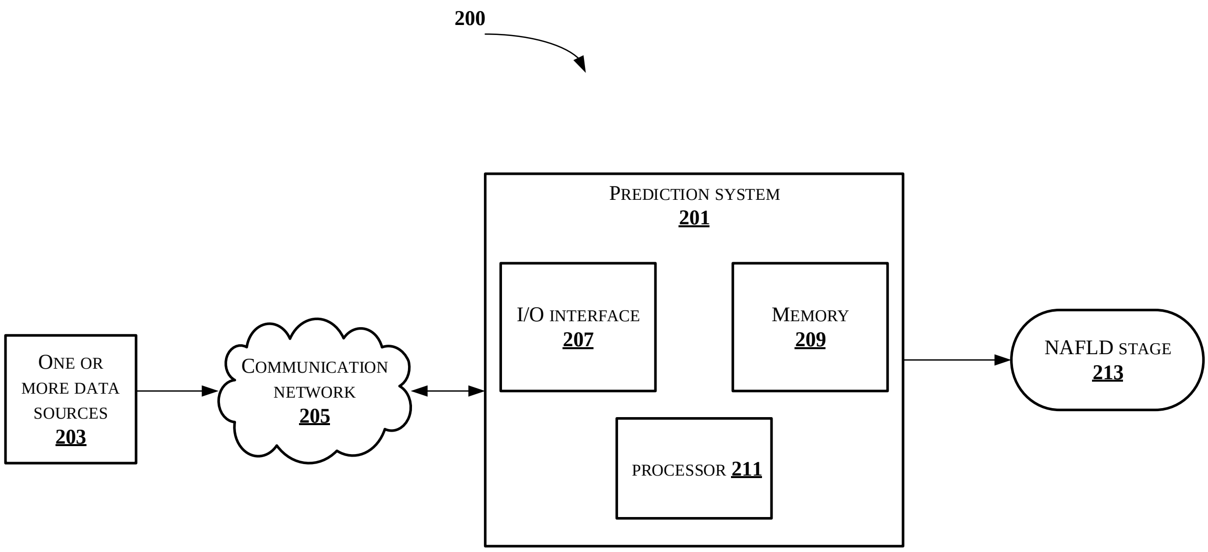

Figure 2

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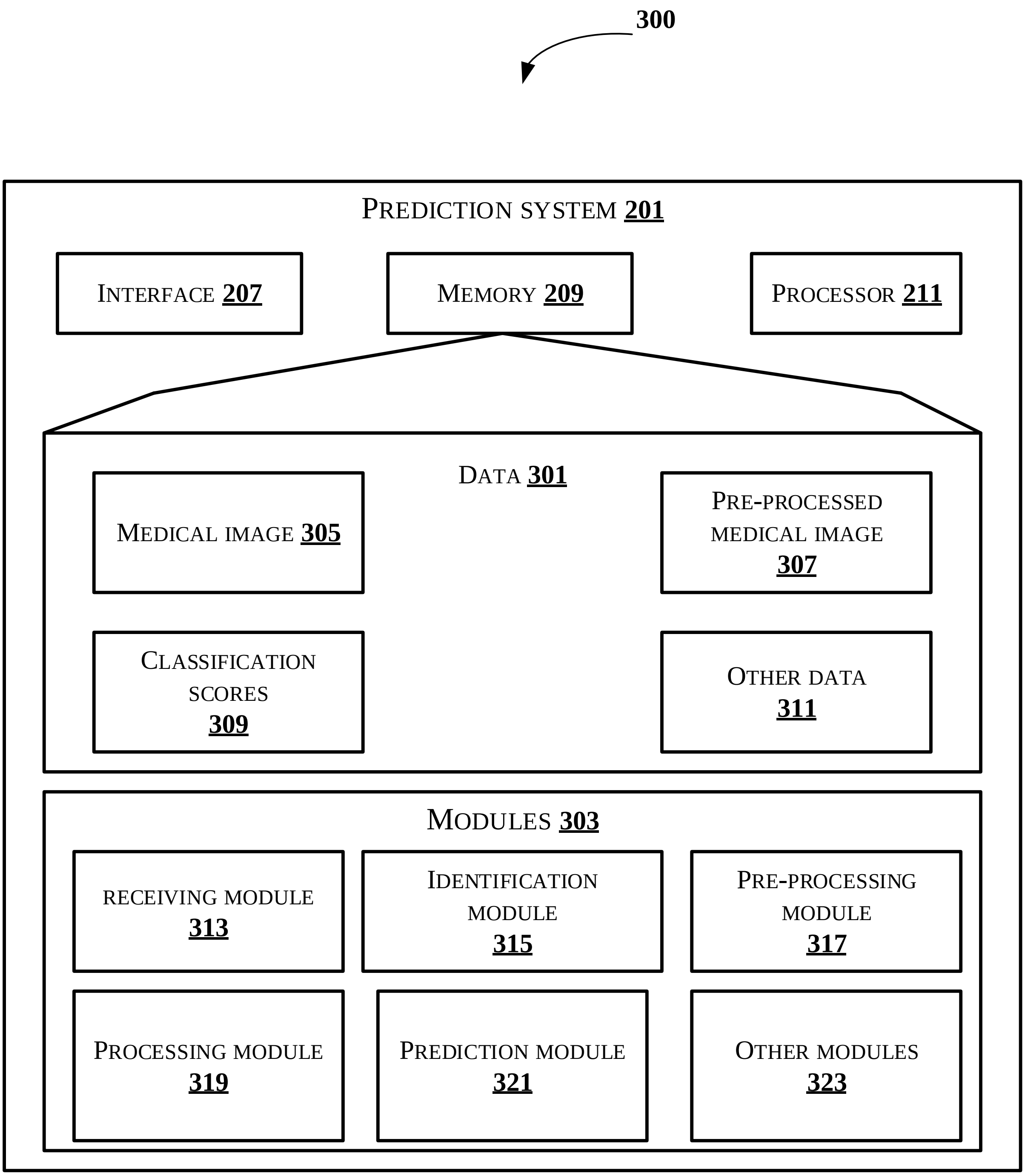

Figure 3

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L&T Technology Services Limited,
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Manapakkam, Chennai - 600089.

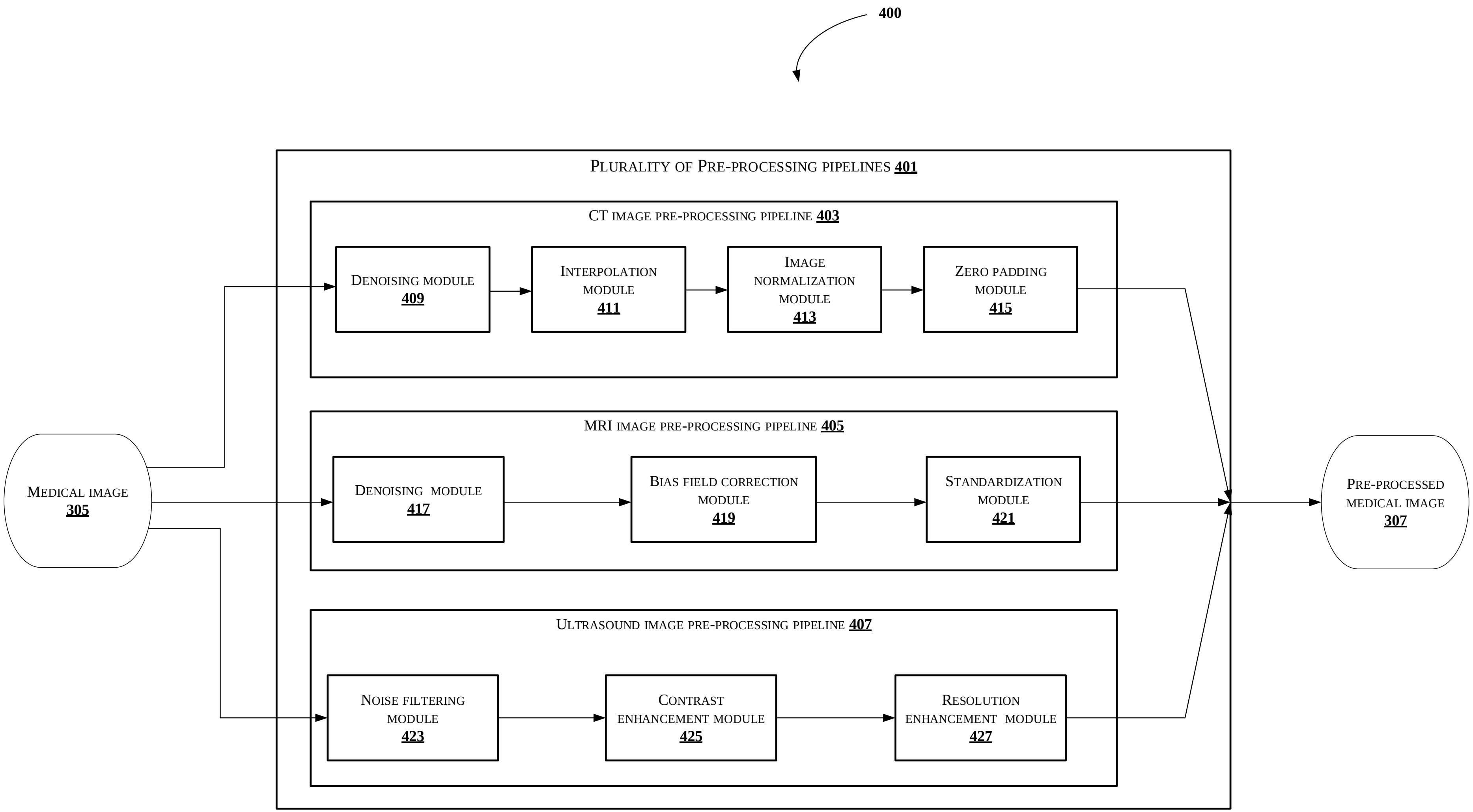

Figure 4

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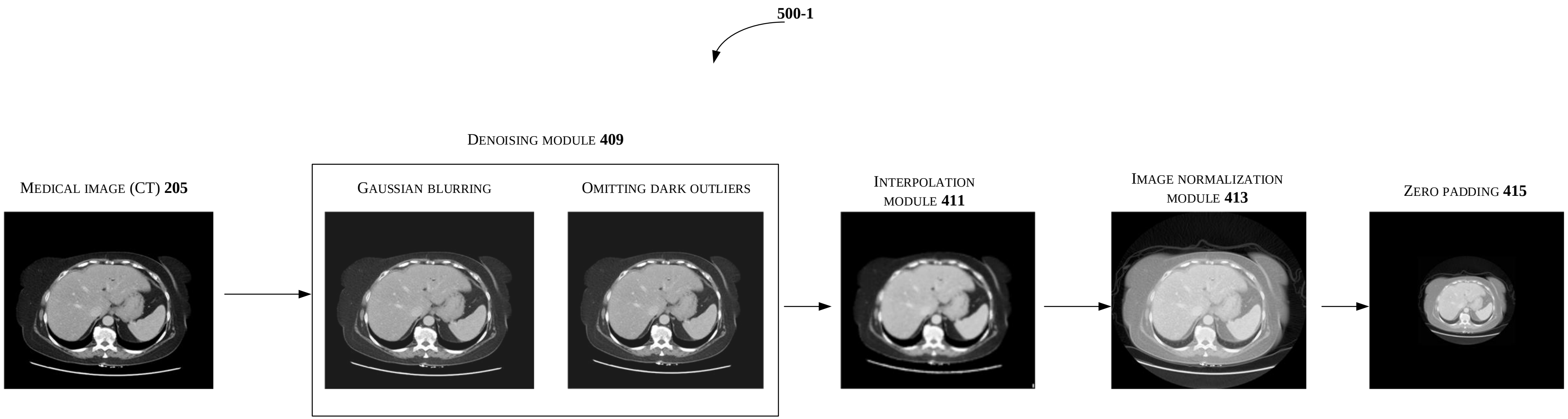

Figure 5A

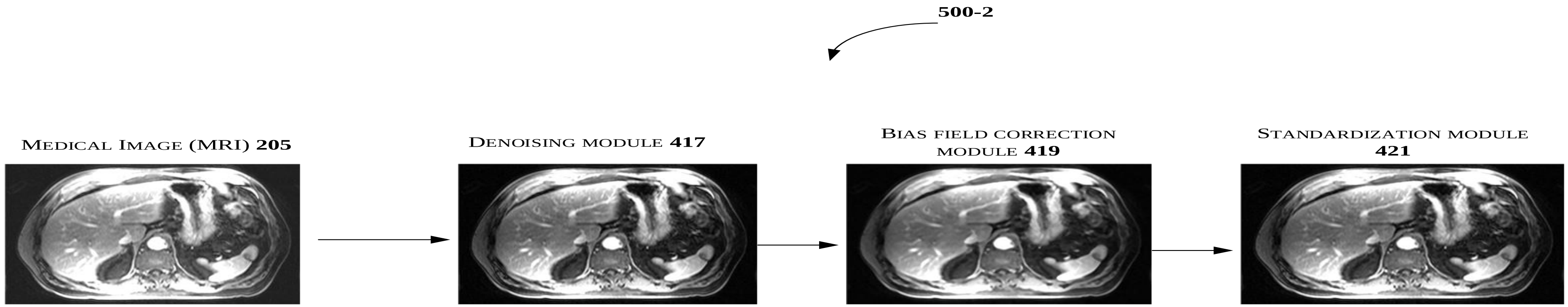

Figure 5B

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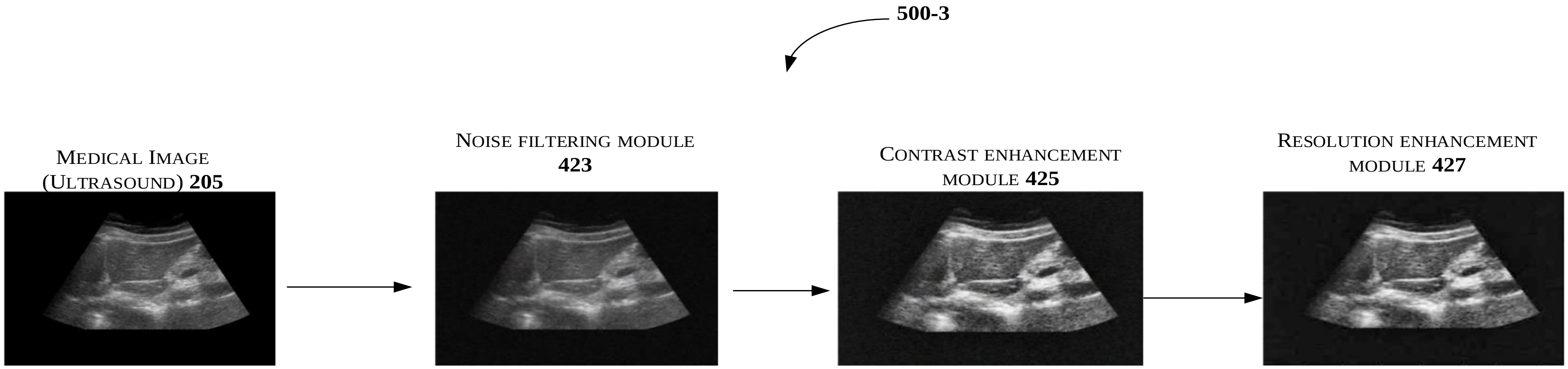

Figure 5C

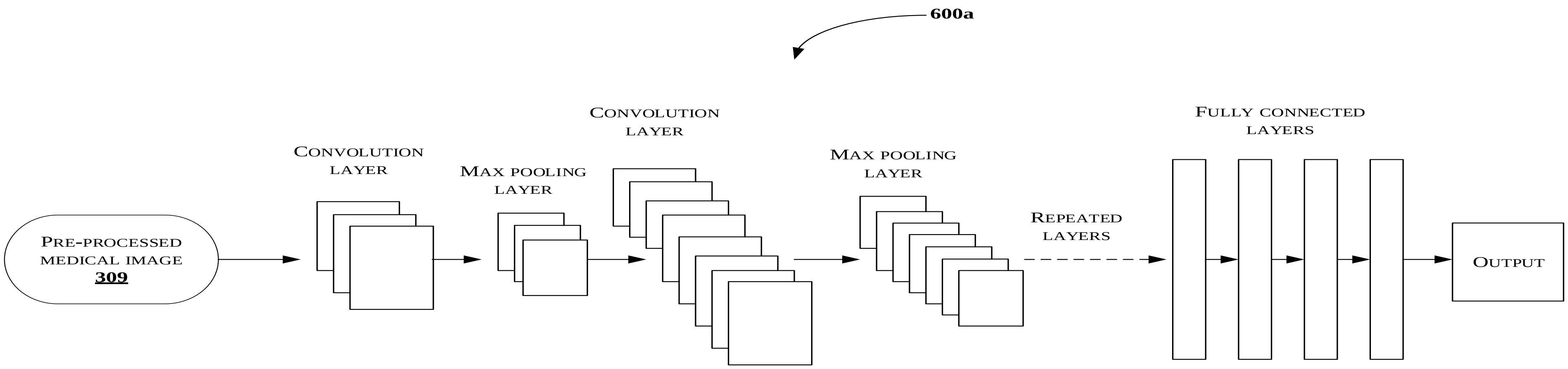

Figure 6A

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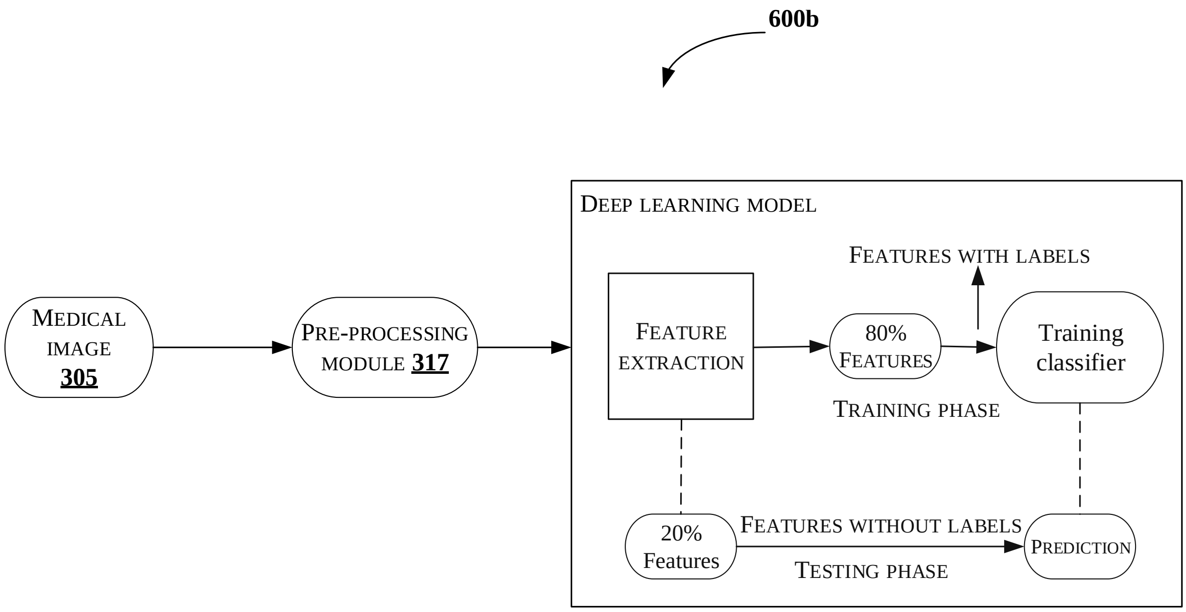
600b
MEDICAL IMAGE 305
PRE-PROCESSING MODULE 317
DEEP LEARNING MODEL
FEATURES WITH LABELS
FEATURE EXTRACTION
80% FEATURES
Training classifier
TRAINING PHASE
20% Features
FEATURES WITHOUT LABELS
PREDICTION
TESTING PHASE

Figure 6B

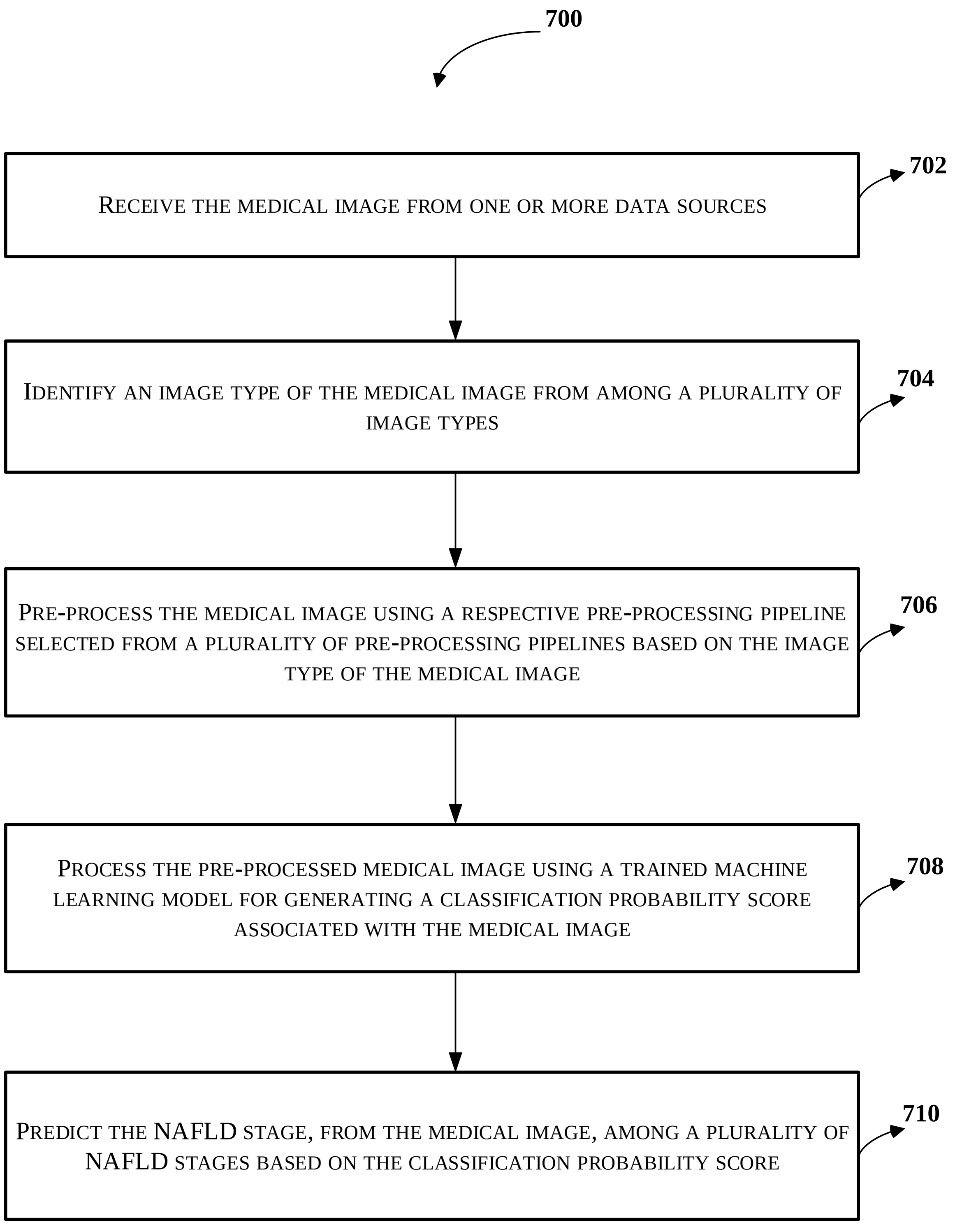

Figure 7

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