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(54) **IMAGE FEATURE CLASSIFICATION**

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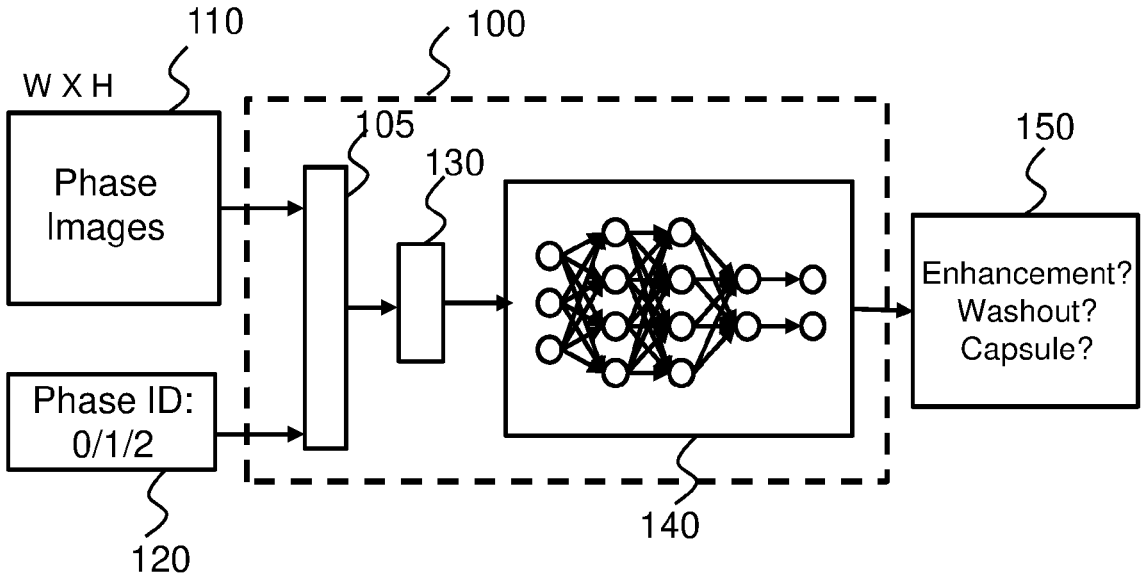
(57) **ABSTRACT**

A method and system for image feature classification using a NN-based learning algorithms to make a decision about a feature in a medical image or image part. In particular, embodiments may make use of a phase of a multi-phasic image to improve classification accuracy. For instance, embodiments may combine different phases of multiphasic images as training data.



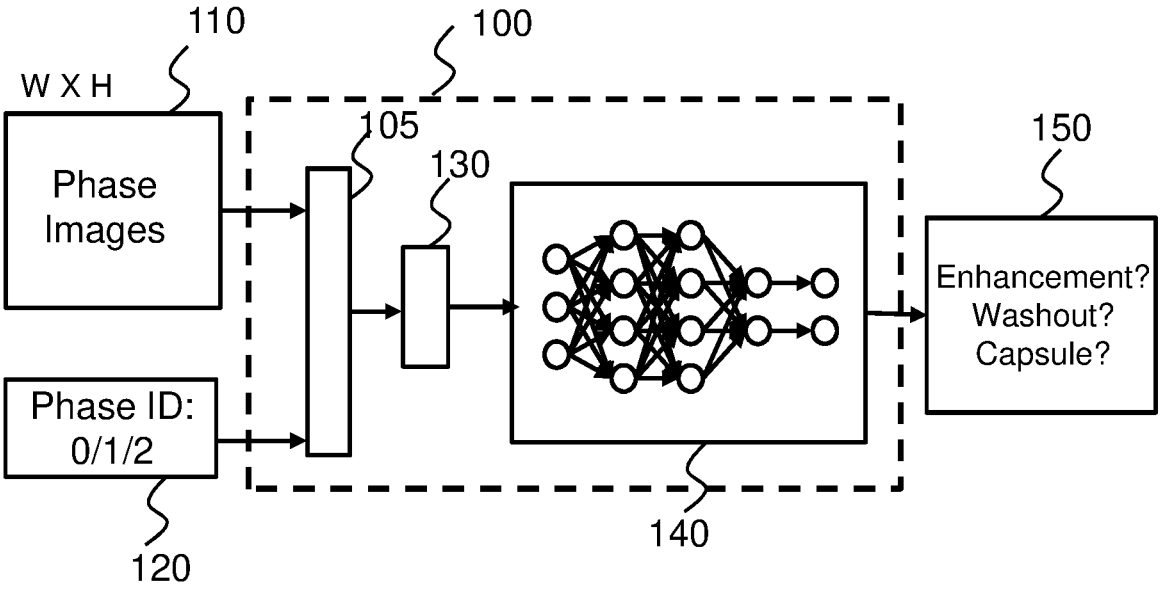

110
100
W X H
105
130
150
Phase Images
Enhancement? Washout? Capsule?
Phase ID: 0/1/2
120
140

FIG. 1

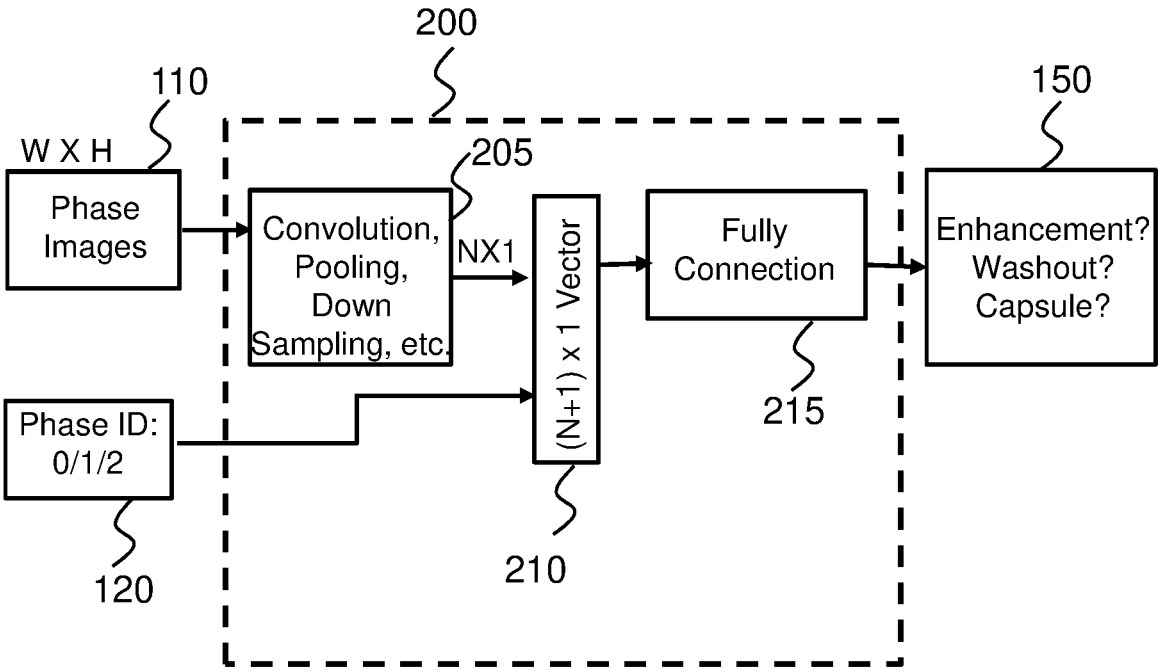

200
110
150
W X H
205
Phase Images
Convolution, Pooling, Down Sampling, etc.
NX1
(N+1) x 1 Vector
Fully Connection
Enhancement? Washout? Capsule?
Phase ID: 0/1/2
215
210
120

FIG. 2

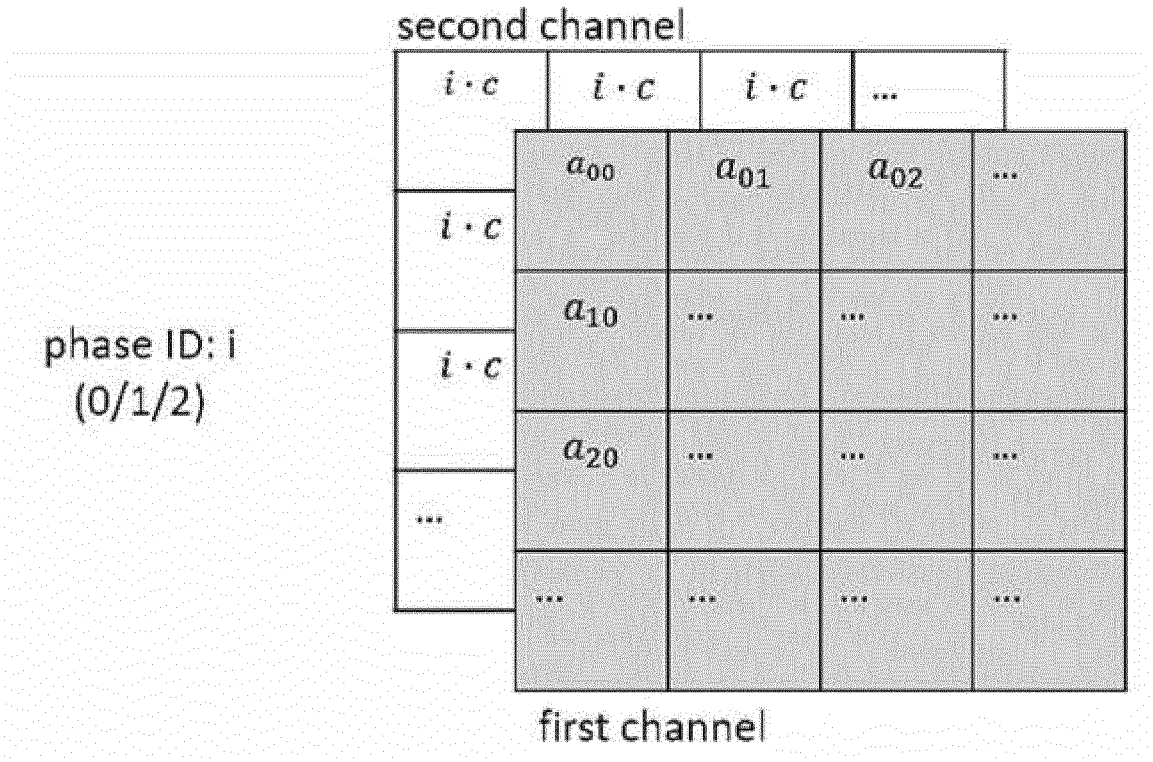

second channel
$i \cdot c$
$i \cdot c$
$i \cdot c$
...
$i \cdot c$
$i \cdot c$
...
a_{00}
a_{01}
a_{02}
...
a_{10}
...
...
...
a_{20}
...
...
...
...
...
...
...
phase ID: i
(0/1/2)
first channel

FIG. 3

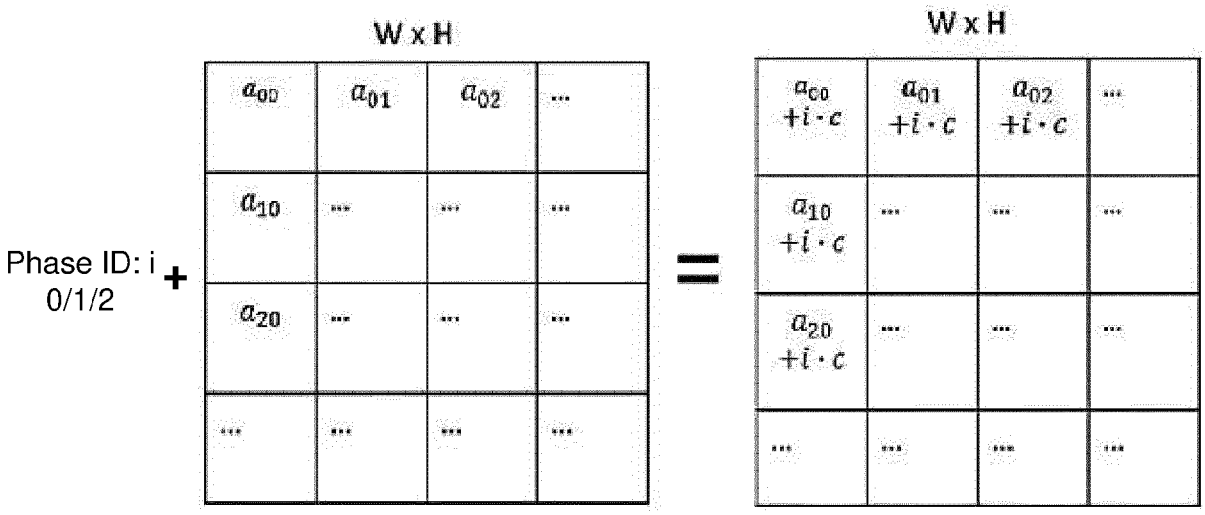

W x H
Phase ID: i
0/1/2
+
=
W x H
a_{00}
a_{01}
a_{02}
a_{10}
a_{20}
$a_{00} + i \cdot c$
$a_{01} + i \cdot c$
$a_{02} + i \cdot c$
$a_{10} + i \cdot c$
$a_{20} + i \cdot c$

FIG. 4A

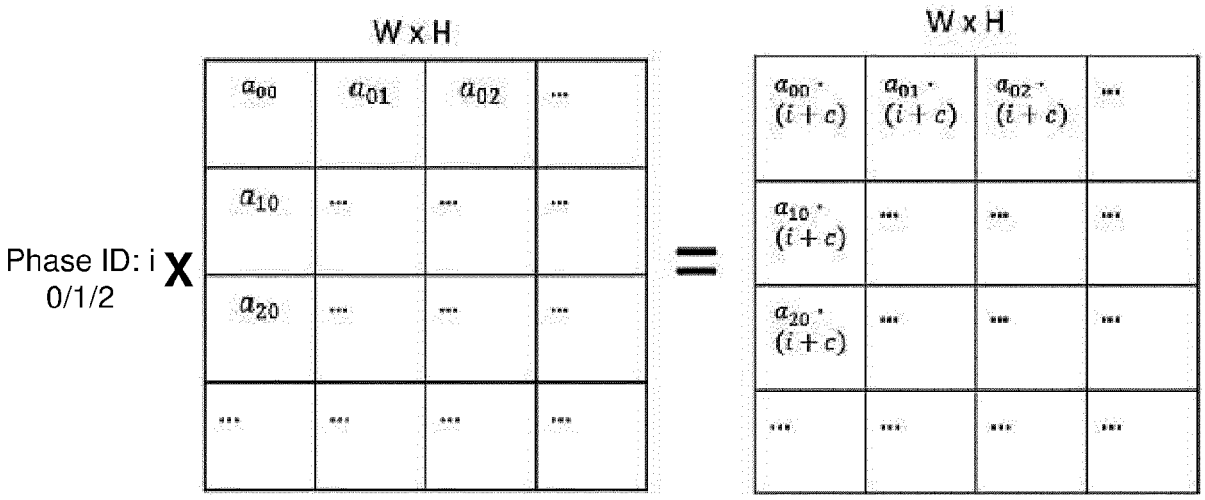


FIG. 4B

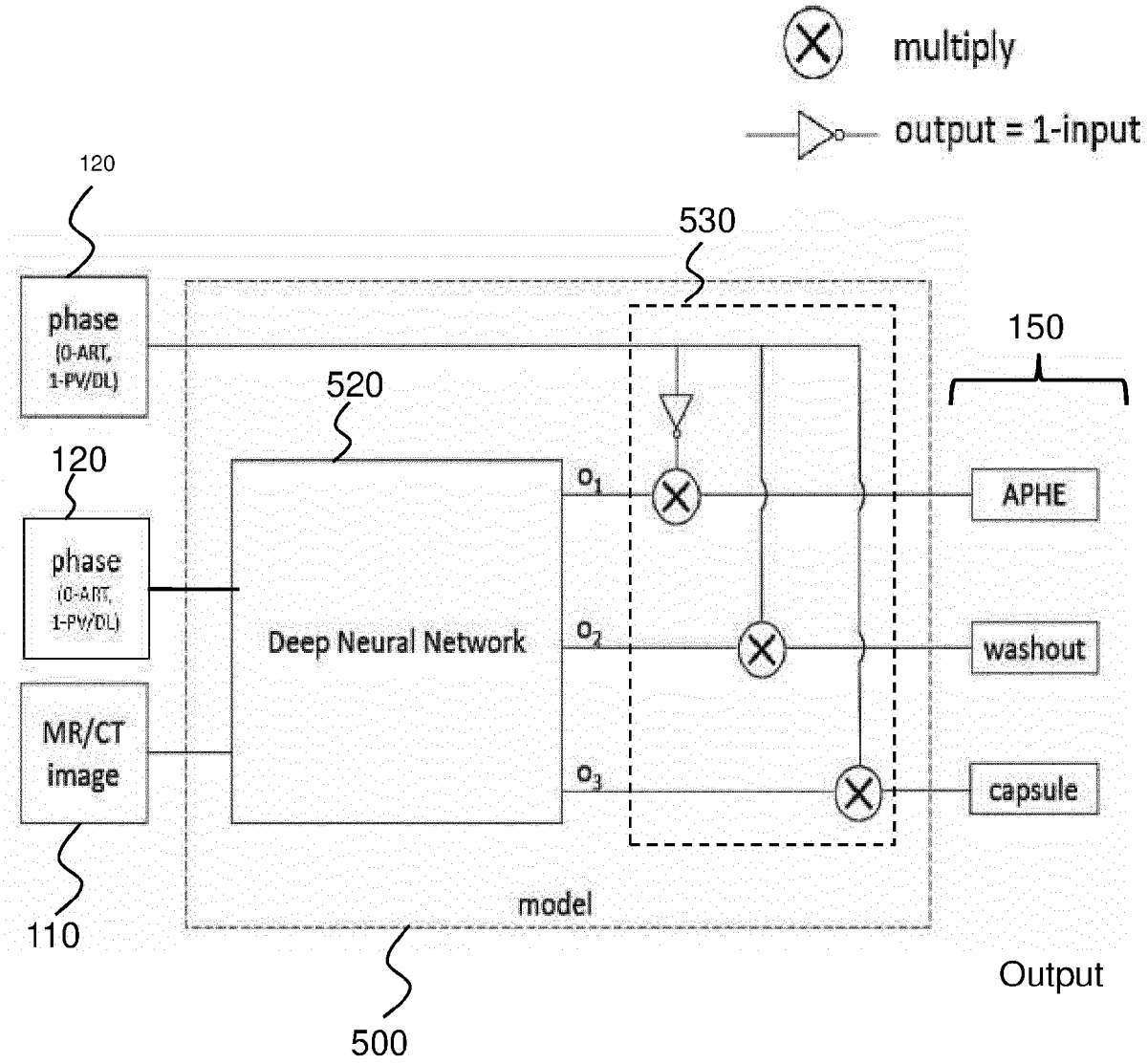

multiply
output = 1-input
120
phase
(0-ART,
1-PV/DL)
530
150
520
120
phase
(0-ART,
1-PV/DL)
Deep Neural Network
o_1
o_2
o_3
APHE
washout
capsule
MR/CT
image
model
110
500
Output

FIG. 5

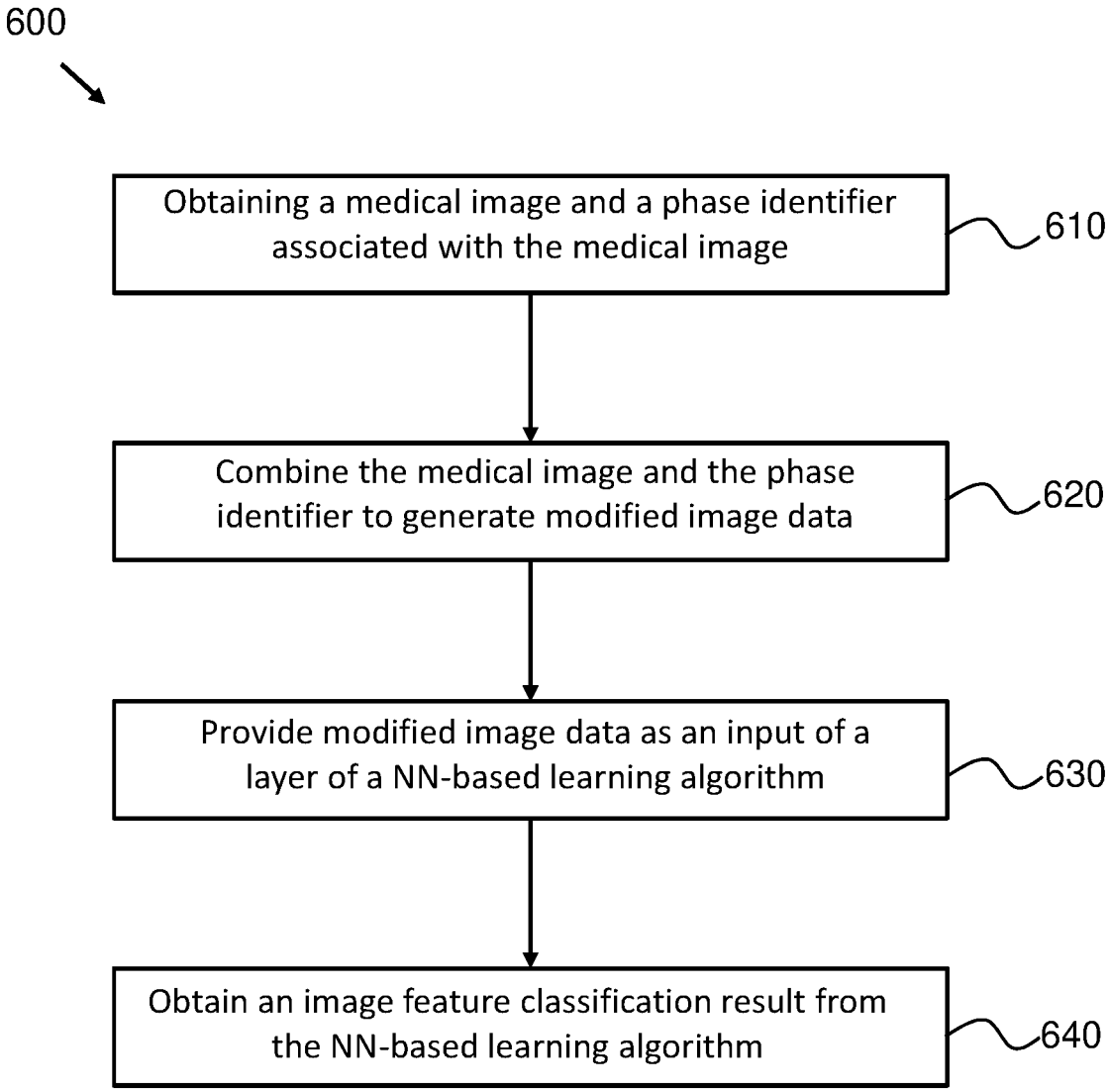

600
Obtaining a medical image and a phase identifier associated with the medical image
610
Combine the medical image and the phase identifier to generate modified image data
620
Provide modified image data as an input of a layer of a NN-based learning algorithm
630
Obtain an image feature classification result from the NN-based learning algorithm
640

FIG. 6

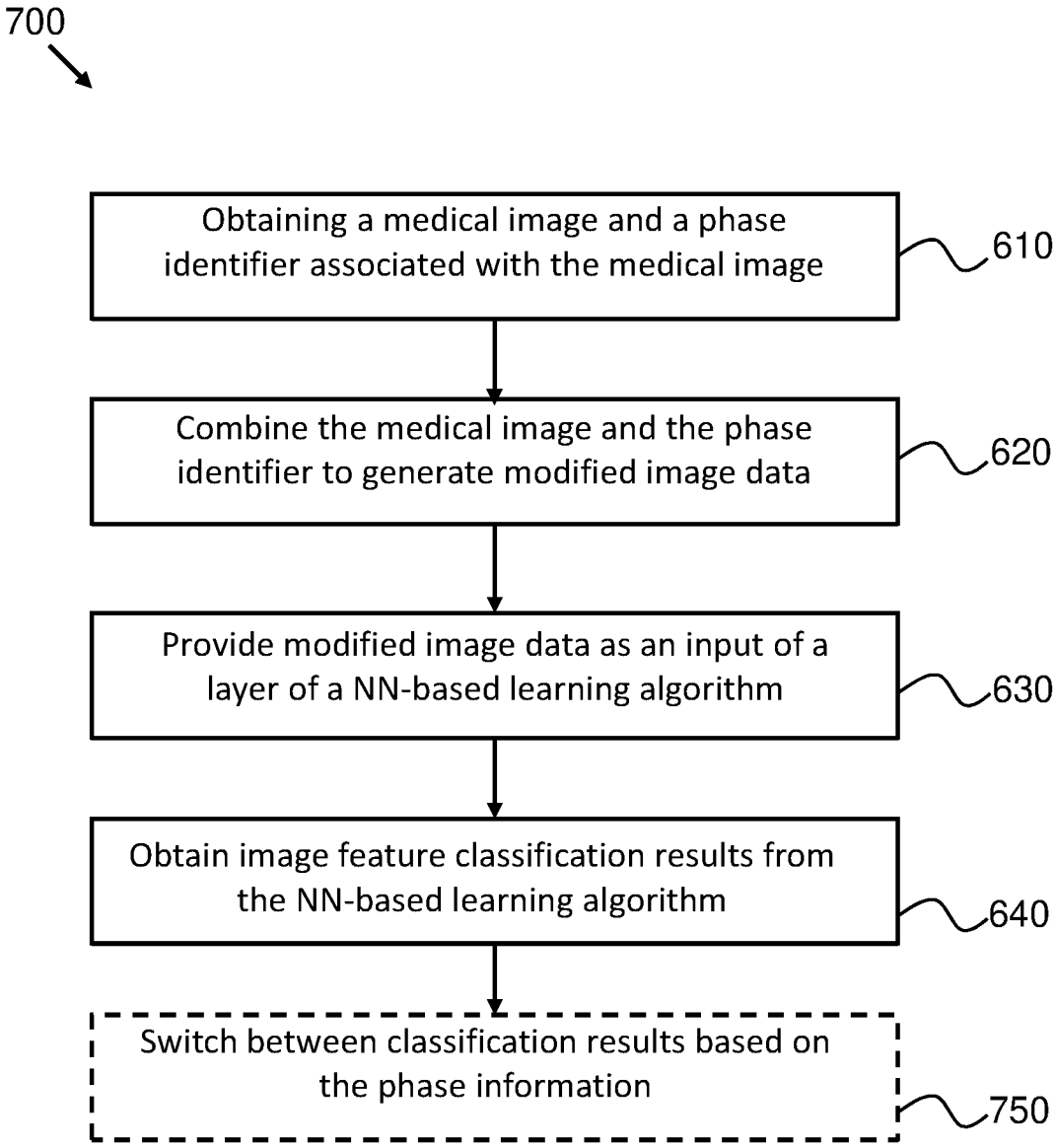

700
Obtaining a medical image and a phase identifier associated with the medical image
610
Combine the medical image and the phase identifier to generate modified image data
620
Provide modified image data as an input of a layer of a NN-based learning algorithm
630
Obtain image feature classification results from the NN-based learning algorithm
640
Switch between classification results based on the phase information
750

FIG. 7

IMAGE FEATURE CLASSIFICATION

FIELD OF THE INVENTION

[0001] The invention relates to the field of image feature classification, and in particular to classifying image features of multi-phasic medical images.

BACKGROUND OF THE INVENTION

[0002] Rapid and reliable detection and diagnosis of medical image features (such as lesions or tumours) may allow for earlier treatment onset and better outcomes for subjects (i.e. patients). As the availability and quality of medical imaging have improved, the need for invasive diagnostic biopsies has decreased, propelling imaging-based diagnosis to a more central role, with a unique status especially for primary liver cancer. However, the radiological diagnosis of potentially malignant hepatic lesions remains a challenging task. For example, enhancement washout or capsule features of medical images are very important, but, because their presence in medical image is typically decided manually (e.g. by a physician), the decision process may be inefficient and/or may result in different decision results across physicians with different expertise or experience.

[0003] Standardized image analysis and reporting frameworks have therefore been developed to improve radiological diagnosis by reducing imaging interpretation variability, improving communication with referring physicians, and facilitating quality assurance and research. A prominent example of such a reporting framework is the Liver Imaging Reporting and Data System (LI-RADS) framework for standardizing the reporting and data collection of CT and MR imaging for hepatocellular carcinoma (HCC).

[0004] However, the increasing complexity of such reporting frameworks have made implementation less feasible in a high-volume practice, leaving an unmet clinical need for computational decision-support tools to improve workflow efficiency. There is therefore a need for a classification assistance system that may be integrated into a clinical workflow to provide physicians with information that will enable them to classify features of multi-phasic medical images more efficiently and with improved confidence.

SUMMARY OF THE INVENTION

[0005] The invention is defined by the claims.

[0006] According to examples in accordance with an aspect of the invention, there is provided a computer-implemented method for classifying image features of multi-phasic medical images. The method comprises: obtaining a medical image and a phase identifier associated with the medical image, the phase identifier representing the phase of the image; combining the medical image and the phase identifier to generate modified image data; providing the modified image data as an input of a layer of a Neural Network, NN,-based learning algorithm configured to classify image features; and obtaining, for the modified image data, an image feature classification result from the NN-based learning algorithm.

[0007] Proposed embodiments provide image feature classification using a NN-based learning algorithms to make a decision about a feature in a medical image or image part (e.g. which includes a lesion). In particular, embodiments may make use of a phase of a multi-phasic image to improve classification accuracy. For instance, embodiments may combine different phases of multiphasic images as training data.

[0008] The NN-based learning algorithm may be trained using a training algorithm configured to receive an array of training inputs and known outputs, wherein the training inputs comprise medical image, medical image segments or medical image features, and wherein the known outputs comprise image feature classifications. In this way, the NN-based learning algorithms may be trained to output an image feature classification when provided with a medical image and a phase identifier associated with the medical image. That is image data and phase data may be combined and, in this way, image data for different phases can be leveraged together for improved training and classification.

[0009] The medical image may, for example, comprise an image of at least a portion of a liver. The NN-based learning algorithm may then comprise a Liver Imaging Reporting and Data System, LI-RADS, feature classifier trained to make a decision about the classification of an image feature.

[0010] In some embodiments, combining the medical image and the phase identifier may comprise: processing the image with an image feature generation algorithm to generate a tensor representing one or more features of the image; and combining the phase identifier with tensor to generate, as the modified image data, a modified tensor. The process of providing the modified image data to a layer of the NN-based learning algorithm may then comprise providing the modified tensor to a hidden layer trained to make a decision about the classification of an image feature.

[0011] By way of example, the hidden layer of the NN may include one layer of the convolution or one layer of the fully connection.

[0012] In an embodiment, combining the medical image and the phase identifier may comprise modifying data of the image based on the phase identifier to generate modified image data. For example, modifying the data of the image may comprise concatenating the phase identifier to the image as an extract channel. In another example, the phase identifier may comprise a numerical value, and modifying the data of the image may then comprises at last one of: adding the numerical value of the phase identifier to pixel values of the image; and multiplying pixel values of the image by the numerical value of the phase identifier. Simple mathematical operations may therefore be employed by embodiments, thus minimizing cost and/or complexity of implementation.

[0013] In some embodiment, obtaining, for the modified image data, an image feature classification result from the NN-based learning algorithm may comprise: obtaining a plurality of image feature classification results from the NN-based learning algorithm; and switching between the plurality of image feature classification results based on the phase identifier so as to select an image feature classification result.

[0014] The medical image may comprise a CT, MR or ultrasound image.

[0015] An exemplary embodiment may comprise the following main elements:

[0016] a first NN layer that is configured to accept multiple-phase images (i.e. multi-phasic images) and the corresponding phase identification numbers as input.

[0017] a second NN layer that combines the image features and the phase identification numbers as a vector; and

[0018] a fully conventional model that receives the combined vector and generates LiRADS features.

[0019] According to examples in accordance with an aspect of the invention, there is provided a computer program comprising code means for implementing the method of any preceding claim when said program is run on a processing system.

[0020] According to another aspect of the invention, there is provided a processing system for classifying image features of multi-phasic medical images. The system comprises: an interface configured to obtain a medical image and a phase identifier associated with the medical image, the phase identifier representing the phase of the image; and a processing unit configured to combine the medical image and the phase identifier to generate modified image data, to provide the modified image data as an input of a layer of a Neural Network, NN,-based learning algorithm configured to classify image features, and to obtain, for the modified image data, an image feature classification result from the NN-based learning.

[0021] In some embodiments, the NN-based learning algorithm is trained using a training algorithm configured to receive an array of training inputs and known outputs, wherein the training inputs comprise medical image, medical image segments or medical image features, and wherein the known outputs comprise image feature classifications.

[0022] There is also proposed a lesion classification system, comprising the system described above and a user interface configured to receive, from the processing system, and display the image feature classification result.

[0023] These and other aspects of the invention will be apparent from and elucidated with reference to the embodiments described hereinafter.

BRIEF DESCRIPTION OF THE DRAWINGS

[0024] For a better understanding of the invention, and to show more clearly how it may be carried into effect, reference will now be made, by way of example only, to the accompanying drawings, in which:

[0025] FIG. **1** is a simplified block diagram of a system for classifying image features of multi-phasic medical images according to an exemplary embodiment;

[0026] FIG. **2** is there is a simplified block diagram of a system for classifying image features of multi-phasic medical images according to another exemplary embodiment;

[0027] FIG. **3** is an illustration depicting a phase identifier "i" being concatenated to an original medical image as an extract channel;

[0028] FIG. **4**A is an illustration depicting the phase identifier "i" being added to the original image values pixel by pixel, where c is a constant number to balance the value ranges of the original image data and the phase number;

[0029] FIG. **4**B is an illustration depicting the phase number "i" (plus a constant c) being multiplied to the original image values pixel by pixel; and

[0030] FIG. **5** depicts a system according to another exemplary embodiment;

[0031] FIG. **6** is a flow diagram of a computer-implemented method for classifying image features of multi-phasic medical images according to an embodiment; and

[0032] FIG. **7** depicts a modification to the embodiment of FIG. **6**.

DETAILED DESCRIPTION OF THE EMBODIMENTS

[0033] The invention will be described with reference to the FIGS..

[0034] It should be understood that the detailed description and specific examples, while indicating exemplary embodiments of the systems and methods, are intended for the purposes of illustration only and are not intended to limit the scope of the invention. These and other features, aspects and advantages of the systems and methods of the present invention will become better understood from the following description, appended claims and accompanying drawings. It should be understood that the same reference numerals are used throughout the FIGS. to indicate the same or similar parts.

[0035] According to a concept of the invention, there is proposed a method and system for classifying image features of multi-phasic medical images. A medical image and a phase identifier associated with the medical image is combined to generate modified image data. The modified image data is provided as an input of a layer of a Neural Network, NN,-based learning algorithm configured to classify image features. An image feature classification result from the NN-based learning algorithm is obtained for the modified image data.

[0036] Embodiments are at least partly based on the realization image data and phase data may be combined (i.e. mixed together) to provide improved training and classification. In this way, an improved deep NN-based LiRADS feature classifier may be realised.

[0037] Illustrative embodiments may, for example, be employed in digital medical imaging platforms as a clinical decision support system. In particular, proposed embodiments may be applicable to liver cancer auto detection systems (especially LiRADS automatic reporting systems).

[0038] FIG. **1** illustrates a system **100** for classifying image features of multi-phasic medical images according to an exemplary embodiment. The system **100** comprises an interface **105** configured to obtain a multi-phasic medical images **110** and a phase identifier **120** associated with each medical image. Here, a phase identifier is a phase identification number which represents the phase of the associated image (e.g. "0" = arterial phase, "1" = portal venous phase, and "2" = delayed phase).

[0039] The system also comprises a processing unit **130** that is configured to combine the medical images and associated phase identifiers to generate modified image data.

[0040] The modified image data is provided as an input of a layer of an artificial Neural Network, NN,-based learning algorithm **140** of the system. Thus, one or more layers of the NN are adapted to receive multiple-phase images (i.e. multi-phasic images) as an input.

[0041] The structure of an artificial NN (or, simply, neural network, NN) is inspired by the human brain. Neural networks are comprised of layers, each layer comprising a plurality of neurons. Each neuron comprises a mathematical operation. In particular, each neuron may comprise a different weighted combination of a single type of transformation (e.g. the same type of transformation, sigmoid etc. but with different weightings). In the process of processing input

data, the mathematical operation of each neuron is performed on the input data to produce a numerical output, and the outputs of each layer in the neural network are fed into the next layer sequentially. The final layer provides the output.

[0042] There are several types of neural network, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs). Embodiments of the present invention employ CNN-based learning algorithms, as CNNs have proved to be particularly successful at analyzing images, and are able to classify images with a much lower error rate than other types of neural network.

[0043] CNNs typically contain several layers, including a convolutional layer, a pooling layer, a fully connected layer and a softmax layer. The convolutional layer consists of a set of learnable filters and extracts features from the input. The pooling layer is a form of non-linear down-sampling, reducing the data size by combining the outputs of a plurality of neurons in one layer into a single neuron in the next layer. The fully connected layer connects each neuron in one layer to all the neurons in the next layer. The softmax layer determines a probability distribution for each output.

[0044] Methods of training a machine-learning algorithm are well known. Typically, such methods comprise obtaining a training dataset, comprising training input data entries and corresponding training output data entries. An initialized machine-learning algorithm is applied to each input data entry to generate predicted output data entries. An error between the predicted output data entries and corresponding training output data entries is used to modify the machine-learning algorithm. This process can be repeated until the error converges, and the predicted output data entries are sufficiently similar (e.g. ±1%) to the training output data entries. This is commonly known as a supervised learning technique.

[0045] For example, weightings of the mathematical operation of each neuron may be modified until the error converges. Known methods of modifying a neural network include gradient descent, backpropagation algorithms and so on.

[0046] The training input data entries for the NN-based learning algorithm **140** used in the system **100** correspond to example medical images, medical image segments or medical image features. The training output data entries correspond to image feature classifications. Thus, the NN-based learning algorithm **140** is configured to classify image features in accordance with its training.

[0047] The images used to train the NN-based learning algorithm **140** may be labeled with three binary numbers to indicate whether there are enhancement, washout, or capsule features. That is, the input training mages each include a lesion and are provides from a lesion segmentation process. The presence of enhancement, washout, or capsule features have been decided from analyzing the output of lesion segmentation process. In this way, the NN-based learning algorithm **140** is trained to decide whether there is enhancement, washout and capsule feature in an image having a detected liver lesion.

[0048] Several pre-processing methods may be employed to improve the training sample. For example, images from the same digital imaging system may be normalized in display features such as gamma correction. An image may be segmented using Otsu's method. This region may then be modified into a standard size.

[0049] The plurality of NN-based learning algorithms may be produced by modifying existing CNN-based learning algorithms, such as VGG, Inception and ResNet.

[0050] From the NN-based learning algorithm **140**, an image feature classification result **150** is obtained for the modified image data. For instance, the algorithm **140** predicts if there are enhancement, washout, or capsule features within the input medical images.

[0051] Referring now to FIG. **2**, there is a depicted a system **200** for classifying image features of multi-phasic medical images according to another embodiment. The embodiment of FIG. **2** differs from that of FIG. **1** in that, in the embodiment of FIG. **2**, the phase identifier of an image is combined with the image after the convolution, pooling and down sampling layers, but prior to the fully connected layer.

[0052] The inputs to the system **200** are a medical image **110** and its associated phase identification number **120**.

[0053] The image **100** can be arterial phase, portal venous phase or delayed phase images generated by CT or MR. The image can be the original slice or just a region of interest (ROI) containing a lesion.

[0054] The corresponding phase identification number is "0", "1" or "2" for arterial phase, portal venous phase and delayed phase, respectively, depending on which phase the image belongs to.

[0055] Accordingly, in this example of FIG. **2**, the input image size is WxH, and the phase number is a scalar number. The input image **110** is first fed into an image feature generation module **205**. The image feature generation module consists of a number of NN layers including convolution, pooling, down sampling, batch normalization, activation, etc. It can be any deep learning classifier backbones without the fully connected layer, like the modules in VGG, ResNet, Inception, etc.

[0056] The image feature generation module **205** generates a vector with the size as Nx1. The phase identification number is then combined (by a processor **210**) with the image feature vector to generate a new vector with the size (N+ 1) x 1.

[0057] This new vector is then provided to the fully connection module **215**. The fully connection module **215** generates the prediction(s) **150** whether there is enhancement/washout/capsule features.

[0058] In the exemplary embodiment of FIG. **2**, images are labelled with clinical relevance, e.g., arterial enhancement for arterial phase, and washout/capsule only in portal venous/delayed phases. Different phases of images can be mixed together for training and different phases of images can leverage each other to train the image feature generation module **205**.

[0059] As depicted in FIG. **1**, an alternative way to combine (e.g. mix) the phase identifier and the medical image data for a classification model is to combine them at the input side of the NN-based algorithm.

[0060] Considering this process of combining a medical image and phase identifier at the input side, it is noted that various different approaches may be employed.

[0061] For example, if the phase identifier is a scalar number, it can be concatenated as an extract channel to the image. Such an approach is depicted in FIG. **3**

[0062] FIG. **3** is an illustration depicting the phase identifier "i" being concatenated to an original medical image as an extract channel. The phase identifier "i" is a scalar number. Specifically, "i" is "0", "1" or "2" for arterial phase,

portal venous phase and delayed phase, respectively, depending on which phase the image belongs to. Further, "c" is a constant number employed to balance the value ranges of the original image data and the phase identifier "i".

[0063] According to another example, the phase identifier may be combined with its associated medical image by being added to the original image value. Such an approach is depicted in FIG. **4**A.

[0064] FIG. **4**A is an illustration depicting the phase identifier "i" being added to the original image values pixel by pixel, where c is a constant number to balance the value ranges of the original image data and the phase number.

[0065] In another example, the phase identifier may be combined with its associated medical image by being multiplied with the original image value. Such an approach is depicted in FIG. **4**B. FIG. **4**B is an illustration depicting the phase number "i" plus a constant "c" being multiplied to the original image values pixel by pixel. Here, c is a constant number for balancing the value ranges of the original image data and the phase number.

[0066] FIG. **5** depicts a system **500** according to another exemplary embodiment. In particular, the system **500** of FIG. **5** is a modified version of the embodiment of FIG. **1**, wherein phase information is further used to implement three switches. In this way, phase information is: (i) added to the image to generate modified image data; and (ii) added as switch information to generate a final result.

[0067] The system comprise a deep NN-based classifier **520** which has three binary outputs as o1, o2 and o3 (for enhancement (APHE), washout, and capsule features, respectively).

[0068] The input of the NN **520** is a greyscale CT or MR image **110** which contains the liver lesion and a phase identifier **120** associated with the image **110**. The image **110** can be from arterial, portal venous or delayed phase. The phase of the image **110** is indicated by the associated phase identifier **120** in the form of binary phase information. The binary phase information is also employed to implement as three switches **530** to control the output of the NN **520**. For the phase variable, value "0" identifies that the input greyscale image is from arterial phase, and value "1" identifies that the input greyscale image is from portal venous or delayed phase.

[0069] The phase identifier is reversed and multiplied with o1 of the NN **520** to provide the final binary output to indicate whether there is enhancement (APHE) feature. Here, reversed means the phase variable is subtracted from '1.

[0070] The phase identified is also multiplied with o2 and o3 of the NN **520**, to provide two binary outputs to indicate whether there are washout and capsule features, respectively.

[0071] During training of the NN **520**, the phase information can select the relevant training error being propagated to the previous layers and switch off the irrelevant training error (e.g. enhancement feature error for portal venous phase image) back propagating. That is, the use of the phase information to implement switches provides the technical effect of controlling error propagation.

[0072] According to the proposed concepts and/or embodiments described, one or more of the following advantages may be provided:

[0073] (i) Different images from different phases may share the same NN, thus enabling the different images to be leveraged for improved learning;

[0074] (ii) Phase information may be considered in the NN-based algorithm, improving prediction; and

[0075] (iii) During training, any difficulty normally associated with labelling the dataset may be reduced. For instance, although washout and capsule features are only meaningful for portal venous and delayed phase images, for an arterial phase image, the washout and capsule labels don't have any impact on the model (since the branches from o2 and o3 to their respective outputs are switched off and the gradient cannot be further back propagated to the other layers).

[0076] By way of yet further example of the proposed concept(s), FIG. **6** is a flow diagram of a computer-implemented method **600** for classifying image features of multiphasic medical images according to an embodiment. In this example, the medical images comprise images of at least a portion of a liver containing a lesion (as detected by a separate lesion detection process for example).

[0077] The method begins with step **610** of obtaining a medical image and a phase identifier associated with the medical image.

[0078] Next, in step **620**, the medical image and the phase identifier are combined to generate modified image data. In this exemplary method, combining **620** the medical image and the phase identifier comprises: processing the image with an image feature generation algorithm to generate a tensor representing one or more features of the image; and combining the phase identifier with the tensor to generate, as the modified image data, a modified tensor.

[0079] Step **630** then comprises providing the modified image data (i.e. the modified tensor) as an input of a hidden layer of a NN-based learning algorithm configured to classify image features. Here, the NN-based learning algorithm comprises a Liver Imaging Reporting and Data System, LI-RADS, feature classifier that is trained to make a decision about the classification of an image feature.

[0080] An image feature classification result is then obtained from the NN-based learning algorithm in step **640**.

[0081] It will be understood that variations may be made to the method depicted in FIG. **6**. For example, as described with reference to the embodiment of FIG. **5**, embodiments may include switching between classification results based on the phase information. By way of illustration, FIG. **7** depicts such a modified embodiment, wherein the method is similar to that of FIG. **6**, but includes the additional step **750** of switching between classification results based on the phase information so as to generate a final result.

[0082] It will also be understood that the disclosed methods are computer-implemented methods. As such, there is also proposed a concept of a computer program comprising code means for implementing any described method when said program is run on a processing system.

[0083] The skilled person would be readily capable of developing a processor for carrying out any herein described method. Thus, each step of a flow chart may represent a different action performed by a processor, and may be performed by a respective module of the processing processor.

[0084] As discussed above, a proposed system may make use of a processor to perform data processing. The processor can be implemented in numerous ways, with software and/or hardware, to perform the various functions required. The processor typically employs one or more microprocessors that may be programmed using software (e.g. microcode) to perform the required functions. The processor may be

implemented as a combination of dedicated hardware to perform some functions and one or more programmed microprocessors and associated circuitry to perform other functions.

[0085] Examples of circuitry that may be employed in various embodiments of the present disclosure include, but are not limited to, conventional microprocessors, application specific integrated circuits (ASICs), and field-programmable gate arrays (FPGAs).

[0086] In various implementations, the processor may be associated with one or more storage media such as volatile and non-volatile computer memory such as RAM, PROM, EPROM, and EEPROM. The storage media may be encoded with one or more programs that, when executed on one or more processors and/or controllers, perform the required functions. Various storage media may be fixed within a processor or controller or may be transportable, such that the one or more programs stored thereon can be loaded into a processor.

[0087] Variations to the disclosed embodiments can be understood and effected by those skilled in the art in practicing the claimed invention, from a study of the drawings, the disclosure and the appended claims. In the claims, the word "comprising" does not exclude other elements or steps, and the indefinite article "a" or "an" does not exclude a plurality. A single processor or other unit may fulfill the functions of several items recited in the claims. The mere fact that certain measures are recited in mutually different dependent claims does not indicate that a combination of these measures cannot be used to advantage. A computer program may be stored/distributed on a suitable medium, such as an optical storage medium or a solid-state medium supplied together with or as part of other hardware, but may also be distributed in other forms, such as via the Internet or other wired or wireless telecommunication systems. If the term "adapted to" is used in the claims or description, it is noted that the term "adapted to" is intended to be equivalent to the term "configured to". Any reference signs in the claims should not be construed as limiting the scope.

1. A computer-implemented method for classifying image features of multi-phasic medical images, the computer-implemented method comprising:

obtaining a medical image and a phase identifier associated with the medical image, the phase identifier representing the phase of the image;

combining the medical image and the phase identifier to generate modified image data;

providing the modified image data as an input of a layer of a Neural Network, NN,-based learning algorithm configured to classify image features; and

obtaining, for the modified image data, an image feature classification result from the NN-based learning algorithm;

wherein combining the medical image and the phase identifier comprises:

processing the image with an image feature generation algorithm to generate a tensor representing one or more features of the image; and

combining the phase identifier with the tensor to generate, as the modified image data, a modified tensor.

2. The computer-implemented method of claim **1**, wherein the medical image comprises an image of at least a portion of a liver having a lesion, and wherein NN-based learning algorithm comprises a Liver Imaging Reporting and Data System, LI-RADS, feature classifier trained to make a decision about the classification of an image feature.

3. The computer-implemented method of claim **1**, wherein the NN-based learning algorithm is trained using a training algorithm configured to receive an array of training inputs and known outputs, wherein the training inputs comprise medical image, medical image segments or medical image features, and wherein the known outputs comprise image feature classifications.

4. The computer-implemented method of claim **1**, wherein comprises:

providing the modified tensor to a hidden layer trained to make a decision about the classification of an image feature.

5. The computer-implemented method of claim **4**, wherein the hidden layer of the NN includes one layer of the convolution or one layer of the fully connection.

6. The computer-implemented method of claim **1**, wherein combining the medical image and the phase identifier comprises:

modifying data of the image based on the phase identifier to generate modified image data.

7. The computer-implemented method of claim **5**, wherein modifying the data of the image comprises concatenating the phase identifier to the image as an extract channel.

8. The computer-implemented method of claim **5**, wherein the phase identifier comprises a numerical value, and wherein modifying the data of the image comprises at last one of:

adding the numerical value of the phase identifier to pixel values of the image; and

multiplying pixel values of the image by the numerical value of the phase identifier.

9. The computer-implemented method of claim **1**, wherein obtaining, for the modified image data, an image feature classification result from the NN-based learning algorithm comprises:

obtaining a plurality of image feature classification results from the NN-based learning algorithm; and

switching between the plurality of image feature classification results based on the phase identifier so as to select an image feature classification result.

10. A non-transitory computer readable medium storing instructions that, when executed by one or more processors, causes the one or more processors to:

obtain a medical image and a phase identifier associated with the medical image, the phase identifier representing the phase of the image;

combine the medical image and the phase identifier to generate modified image data;

provide the modified image data as an input of a layer of a Neural Network, NN,-based learning algorithm configured to classify image features; and

obtain, for the modified image data, an image feature classification result from the NN-based learning algorithm;

wherein combining the medical image and the phase identifier comprises:

processing the image with an image feature generation algorithm to generate a tensor representing one or more features of the image; and

combining the phase identifier with the tensor to generate, as the modified image data, a modified tensor.

11. A system for classifying image features of multi-phasic medical images, the system comprising:

an interface configured to obtain a medical image and a phase identifier associated with the medical image, the phase identifier representing the phase of the image; and

a processing unit configured to combine the medical image and the phase identifier to generate modified image data, to provide the modified image data as an input of a layer of a Neural Network, NN,-based learning algorithm configured to classify image features, and to obtain, for the modified image data, an image feature classification result from the NN-based learning,

wherein combining the medical image and the phase identifier comprises:

processing the image with an image feature generation algorithm to generate a tensor representing one or more features of the image; and

combining the phase identifier with tensor to generate, as the modified image tensor, a modified tensor.

12. The system of claim **11**, wherein the NN-based learning algorithm is trained using a training algorithm configured to receive an array of training inputs and known outputs, wherein the training inputs comprise medical image, medical image segments or medical image features, and wherein the known outputs comprise image feature classifications.

13. The system of-any-ef claims **11**, wherein

providing the modified image data to a layer of the NN-based learning algorithm comprises:

providing the modified tensor to a hidden layer of the NN trained to make a decision about the classification of an image feature.

14. The system of claim **11**, wherein combining the medical image and the phase identifier comprises:

modifying data of the image based on the phase identifier to generate modified image data.

15. A lesion classification system, comprising:

the system of claim **10**; and

a user interface configured to receive, from the processing system, and display the image feature classification result.

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