

**METHODS AND SYSTEMS FOR AUTOMATED ANALYSIS OF MEDICAL IMAGES
WITH INJECTION OF CLINICAL RANKING**

Cross-Reference to Related Applications

- 5 The present application claims priority from Australian Provisional Patent Application No 2021903432 filed on 27 October 2021, the contents of which are incorporated herein by reference in their entirety.

Field of the Invention

- 10 The present invention generally relates to computer-implemented methods for analysing medical images, as well as computing systems, services, and devices implementing the methods. Embodiments of the invention improve on analysis of medical images by providing injection of clinical ranking during automated analysis of medical images employing machine learning techniques, in particular deep learning
15 networks, such as convolutional neural networks, trained using sub-stratification training. Methods, systems, services, and devices embodying the invention find applications, amongst others, in the clinical assessment of chest conditions such as pneumothorax and other radiological findings pertaining to the chest or head.

20 **Background to the Invention**

- Generally, the manual interpretation of medical images performed by trained experts (such as e.g. radiologists) is a challenging task, due to the large number of possible findings that may be found. For example, the chest x-ray (CXR) is a very commonly
25 performed radiological examination for screening and diagnosis of many cardiac and pulmonary diseases. CXRs are used for acute triage as well as longitudinal surveillance. In other words, a CXR is typically examined for any detectable abnormality in addition to the clinical indication for which it was ordered. This means that radiologists must be alert to identify many different conditions, with a concordant
30 risk that some findings may be missed.

CXRs are particularly difficult to interpret. Additionally, the increasing demand for specialists that are qualified to interpret medical images (i.e. medical imaging specialists or expert radiologists) far outweighs the availability of these specialists. Furthermore, the training of new specialists requires a significant amount of time. As a
5 result, technical operators, such as radiographic technicians/ radiographers, are increasingly called upon to provide preliminary interpretations to decrease the waiting time and/or to provide a triage assessment. However, the accuracy and confidence in the work of such technicians is generally inferior to that of highly-trained and highly-experienced specialists.

10

Empirical training has been used to assess medical imagery, in which mathematical models are generated by learning a dataset. Deep learning is a particularly data-hungry subset of empirical training that is itself a subset of artificial intelligence (AI). Recently, the use of deep learning approaches to generate deep neural networks
15 (DNNs) which are also known as deep learning models, that automate the assessment of CXR images has been suggested. PCT/AU2021/050580 entitled "SYSTEMS AND METHODS FOR AUTOMATED ANALYSIS OF MEDICAL IMAGES" by the same applicant, Annalise-AI Pty Ltd, the contents of which are incorporated in its entirety, describes improved technology in analysing anatomical images using deep learning
20 models.

Prior methods have indicated the presence (and confidence of such prediction) of a radiological finding among a list of findings without any indication of priority of clinical significance of the prediction generated by an AI model 718. There is an ongoing need
25 for improved methods to communicate the results to user systems and user devices in a manner that efficiently produces clinically useful outputs for clinical decision support and exhibiting performance that is non-inferior to conventional unassisted prior methods.

30 Baltruschat, I. et al., 'Smart chest X-ray worklist prioritization using artificial intelligence: a clinical workflow simulation', European Radiology, Vol. 31, No. 6, 2021 discloses a simulation framework that models the current workflow at a university hospital by incorporating hospital-specific CXR generation rates and reporting rates and pathology distribution. In particular, this document discloses ranking of pathologies.

US9386084 B1 discloses systems and methods that allow transfer criteria to be defined based on one or more of several attributes, such as a particular user, site, or device, as well as whether individual images and/or image series are classified as thin
5 slices, and applied to medical images in order to determine which images are downloaded, viewed, stored, and/or any number of other actions that might be performed with respect to particular images.

Annarumma, M. et al, 'Automated triaging of adult chest radiographs with deep artificial
10 neural networks', Radiology, Vol. 291, No. 1, 2019 discloses an AI system, based on deep convolutional neural networks (CNNs), for automated real-time triaging of adult chest radiographs on the basis of the urgency of imaging appearances.

In various embodiments the present invention seeks to address, individually and/or in
15 combination, one or more of the foregoing needs and limitations of the prior art.

Summary of the Invention

According to a first independent aspect of the invention, there is provided a method
20 comprising the steps of:

providing a plurality of visual findings in one or more anatomical images of a subject, wherein the plurality of visual findings are generated using a convolutional neural network (CNN) component of a neural network, wherein a subset of the generated visual findings represents a set of priority findings;
25 providing a first classification list for the plurality of visual findings, to associate a first clinical ranking to the set of priority findings, respectively;
providing a second classification list wherein the second classification list is user configurable;
assigning a clinical ranking to the set of priority findings, using at least one of
30 the first and second classification lists;
combining the set of priority findings and their assigned clinical ranking, respectively to form triage data; and

communicating the triage data to a user system configured to process the triage data and to generate, using the triage data, an output that represents a re-ordered workload.

- 5 The set of priority findings represents a subset of the generated visual findings and the triage data (and remainder of the triage process) is only based on this subset of generated visual findings.

10 In embodiments of the invention, the visual findings may be radiological findings in anatomical images comprising one or more chest x-ray (CXR) images or computed tomography (CT) images.

15 In a dependent aspect, the second classification list takes precedence over the first classification list. In a further dependent aspect, where the clinical ranking is assigned using both the first and second classification lists, assigning the clinical ranking comprises the steps of: obtaining a first ranking value for a priority finding using the first classification list, obtaining a second ranking value for said priority finding using the second classification list, and providing the second ranking value as the assigned clinical ranking only if the second ranking value is equal to or higher than the first ranking value. The priority findings are then referred to as assignable findings where an assign response is triggered. In other words, the priority findings have been upgraded.

25 Preferably, the triage data comprises ranking values respectively assigned to each possible "assign response" to ensure the highest ranking value is returned where more than one assignable finding is detected.

30 The first and second classification lists correspond to two types of clinical rankings, the first one being a 'default' priority list that is fixed and non-adjustable by the manufacturer or vendor of the software, whilst the second one is a user defined list that represents a user's workload. Either or a combination of both may be applied to obtain the clinical ranking. When applied in combination, in preferred embodiments, the second classification list takes precedence, such that a default priority value is only updated if the assigned clinical ranking would result in an upgrade in the user's workload.

35

Advantageously, prioritisation of the visual findings is made possible according to embodiments of the invention which generates predictions from one or more deep learning models, looking ahead before the human user (i.e. radiologist), and predicting what is more clinically or medically significant for the human radiologist to consider first
5 temporally. This is in contrast to existing methods which merely assign rankings based on the date/time a patient performs their CXR or other radiological scan, which may be a simple queue based only on time of scan – first come first serve, for example. This is important because some diseases or injuries are time critical and need to be reviewed as soon as possible, otherwise permanent damage to the patient could occur
10 or accelerated deterioration of the patient's medical condition may occur, while other findings are not as time sensitive (i.e. a finding such as tumours). Further advantageously, the second classification is customisable by the user or user system, increasing flexibility and configurability of the system to account for various patient care settings and use cases unique to the user's operational environment.

15 In a dependent aspect, the triage data comprises an indication of priority findings from the plurality of priority findings that correspond to only one of the group of:
said priority findings, priority findings that have been assigned a clinical value (i.e. assignable findings or priority findings with an assign response), a priority finding that
20 has been assigned a highest clinical ranking. It will be appreciated that the priority finding that has been assigned a highest clinical ranking may be from a plurality of priority findings that have been assigned the same highest clinical ranking (i.e. a group of such priority findings).

25 In a dependent aspect, the method further comprises the step of: using the triage data to update a user's worklist corresponding to the plurality of visual findings. The user's worklist may comprise at least one study such as a medical study. Preferably the triage data corresponds to a study for a single patient.

30 In a dependent aspect, updating the user's worklist is configurable to use only one of the group of: said priority findings, priority findings that have been assigned a clinical value (i.e. assignable findings), a priority finding that has been assigned a highest clinical ranking. It will be appreciated that the priority finding that has been assigned a

highest clinical ranking may be from a plurality of priority findings that have been assigned the same highest clinical ranking (i.e. a group of such priority findings).

In a dependent aspect, the triage data is provided in a JavaScript Object Notation (JSON) format. In a further dependent aspect, communicating the triage data comprises converting the triage data to a Health Level 7 (HL7) format. This enables the user system to receive the triage data including a field that allows for the assigned clinical ranking to be stored in, enabling automated communication of the findings in order of their priority, in a more robust and reliable manner.

In a dependent aspect the plurality of visual findings and associated first clinical ranking are provided by a server module to an integration layer module. Preferably, the visual findings and associated first clinical ranking are provided using a WebSockets protocol. The integration layer module increases flexibility and configurability of the system 10, whilst the WebSockets protocol provides a security benefit.

In a dependent aspect the integration layer module comprises a database for storing the triage data for a period of time which is configurable by the user. This improves on data security aspects of the system.

In a further aspect, there is provided a system for transmitting triage data for a plurality of visual findings in one or more anatomical images of a subject, wherein the plurality of visual findings are generated using a convolutional neural network (CNN) component of a neural network, the system comprising: at least one processor; and at least one computer readable storage medium, accessible by the processor, comprising instructions that, when executed by the processor, cause the processor to execute a method as described above.

In a further aspect there is provided a non-transitory computer readable storage media comprising instructions that, when executed by at least one processor, cause the processor to execute a method as described above.

Preferred features of each one of the independent claims are provided in the dependent claims.

Brief Description of the Figures

Aspects of the present invention will now be described, by way of example only, with
5 reference to the accompanying figures, in which:

Figure 1 is a block diagram of an exemplary architecture of a medical image analysis system embodying the invention;

Figure 2 is a signal flow diagram illustrating an exemplary method for processing of
10 imaging study results within the embodiment of Figure 1; and

Figure 3 is another signal flow diagram illustrating an exemplary method for processing of imaging study results within the embodiment of Figure 1.

Detailed Description

15 Exemplary systems and methods for analysing radiological findings generated by an AI model on given radiology images (e.g. CXR) are described. Referring to Figures 1 and 2, a system 10 comprises modular system components in communication with each other, including a server system 70 configured to send predicted radiological
20 findings associated with a clinical ranking or medical significance rank via an integration layer module 702. The integration layer module 702 includes at least one local database 792a, 792b and a processor 800.

The system 10 further comprises a radiology image analysis server (RIAS) 110. The
25 integration layer 702 may receive worklist priority data from the RIAS 110 representing a user's worklist for a radiologist (i.e. a user), along with associated data which includes a patient identification (ID) and customer account number for example. The predicted radiological findings together with clinical ranking data are provided via the integration layer 702 comprising integrator services, the integration layer 702 connecting to an
30 injection layer 50, the clinical ranking data being processable by the RIAS 110, advantageously communicating to the RIAS 110 the predicted AI radiology findings in a timely manner. This enables a more reliable and safer method of processing predicted radiological findings than known methods, which is particularly important when the radiological findings relate to diseases or injuries which are time critical and

need to be identified and confirmed in a timely manner to prevent or minimise permanent injury or accelerated deteriorating medical condition(s) of a patient.

There are two types of clinical rankings that may be applied against a predicted
 5 radiological finding generated by the AI model 718: a “priority scale” which represents
 a first classification or default list (default priority parameter values) and an “assign
 scale”, which represents a second classification list that is a customer defined list.
 Either of these types of clinical rankings, or a combination of both may be applied to
 the radiological findings generated by the AI model 718; when in combination, the
 10 “assign scale” takes precedence over the priority scale.

Accordingly, the scales representing worklist priority levels may be customisable per
 user (i.e. a radiologist or radiographer): for example, user A priority is “Standard,
 Urgent, Critical” corresponding to ranks 3, 2, 1 respectively which is being processed
 15 and mappable by the system 10, while user B may be “Very Low, Med, High, Very
 High” (ranks 3,2,1, respectively) can also be accommodated for. It will be appreciated
 that priority levels may be given any suitable values, and can be renamed to any
 alphanumeric string. Additional levels can also be created.

20 The code snippets below represent exemplary implementations:

```

    • "assign": {
    •   "priorities": [
    •     {
    •       "assignPriorityId": 1,
    25   •       "rank": 1,
    •       "priority": "10"
    •     },
    •     {
    •       "assignPriorityId": 2,
    30   •       "rank": 2,
    •       "priority": "20"
    •     },
    •     {
    •       "assignPriorityId": 3,
    35   •       "rank": 3,
    •       "priority": "30"
    •     }
    •   ],
    •
  
```

40 "priority": "10" is the value that is injected into the RIAS 110 via the injection
 layer 50.

- 10 = Critical
- 20 = Urgent
- 30 = Standard

"rank": 1 - internal rank for software to know priority.

```

5      • "assignPriorityId": 1 - This id
      • "labels": [
      •   {
      •     "label": "abdominal_clips",
      •     "groupid": 2,
10    •     "displayOrder": 29,
      •     "features": {
      •       "assign": true,
      •       "assist": true,
      •       "assure": false
15    •     },
      •     "assignPriorityId": 1
      •   },
      •   {
      •     "label": "acute_aortic_syndrome",
20    •     "groupid": 1,
      •     "displayOrder": 43,
      •     "features": {
      •       "assign": true,
      •       "assist": true,
25    •       "assure": false
      •     },
      •     "assignPriorityId": 1
      •   },

```

30 Advantageously, the system 10 enables injection of clinical priority levels into the RIAS worklist. This requires the system architecture to be integrated with the RIAS 110 to communicate the predicted radiological findings in a more robust and reliable manner.

Referring to Figure 2, at step 80, the predicted radiological findings together with
 35 assigned clinical ranking data are sent to the integration layer 702 and stored in the database 792a before being queued to the processor 800. The processor 800 may check, at step 82, if the predicted radiological findings are "white-listed" for the RIAS 110. A white-list may be assigned for example using a Digital Imaging and Communications in Medicine (DICOM) tag for the user institution (RIAS) name. It
 40 would be possible to select system functionality by enabling or disabling the priority assign functionality; this increases system flexibility and configurability. At step 84, the processor 800 determined the priority of the radiological findings, and maps the findings to the priority, as described above.

At step 56,86, the processor 800 sends the study priority payload comprising the predicted radiological finding and assigned priority data to the injection layer 50 which functions to convert data in a format processable by the RIAS 110. At step 87, the
5 injection status is communicated back to the integration layer 702, and forwarded, at step 88, by the integration layer 702 to the server 70.

If the associated priority for a predicted radiological finding would result in an upgrade in the user's worklist- then a new priority is assigned, at step 84, to the predicted
10 radiological finding. The predicted radiological findings with a new priority assigned are said to be associated with an "assign response". In this way, no predicted radiological finding will be assigned a downgraded priority in this example. In some embodiments, the priority value is updated at step 84 where the predicted radiological finding is determined to be present in the study. Where more than one predicted radiological
15 finding with an assign response is detected in a study, the highest ranking response, as defined by a worklist user configuration is returned. It will be appreciated that in alternative envisaged processes, a predicted radiological finding may be assigned a downgraded priority; in other words, in alternative envisaged configurations, the first classification list would take precedence over the second classification list representing
20 the default user worklist as defined above.

Accordingly, the integration layer 702 may receive the worklist priority from the RIAS 110 and only apply the new priority value when the original worklist priority is lower. It will be appreciated that, in some cases, the original worklist priority data may not be
25 available; i.e. there is no mechanism to obtain worklist priority levels from the RIAS 110. In these cases, the predicted radiological findings may be selected by the highest available priority, e.g. "Critical". Accordingly, the priority value injected to the RIAS 110 will only be the highest, thus the original unknown priority level will remain the same or be increased; in other words, there will be no downgrading of study priority. This
30 increases safety and reliability of the system 10.

In preferred embodiments, priority changes are tracked for predicted radiological findings where the original priority value was predicted by the RIAS 110. For example, the number of predicted radiological findings where priority has changed can be

tracked, together with the before values predicted by the RIAS 110 and the after (updated values) updated at step 94; the number of predicted radiological findings where priority has not been updated and remains unchanged is also tracked.

- 5 Preferably, the data in the assign response indicates the predicted radiological findings that have triggered the assign priority response for one or more of the following scenarios: just the priority findings, just the assignable findings, just the one finding that set the highest priority (or from the highest group if there are more than 1 highest in the group). Preferably, a rank value of each possible assign response should be
10 included to ensure the highest rank response is returned when more than one assign enabled finding is detected.

The study worklist priority update is preferably configurable to respond to: just the priority findings, just the assignable findings, just the one finding that set the highest
15 priority (or from the highest group if there are more than 1 highest in the group), just a subset of studies based on site/facility filtering.

The system 10 further comprises an injection layer 50 to transmit the data to the RIAS 110 in a processable format; in the present example this is a "NextGen™ Connect"
20 module referred to as a MIRTH™ module converting data from a JavaScript Object Notation (JSON) format to Health Level 7 (HL7) format.

Each JSON file received from the integration layer 702 by the injection layer 50 may correspond to a single patient study, e.g. a CXR for one patient. In an example, the
25 JSON payload may contain the following fields: accession number, study instance uid, priority value, rank value, patient information, patient name, patient ID, patient sex, patient date of birth, predicted radiological findings, priority findings, assigned findings, product details, software version, unique device identification (UDI), user guide URL, manufacturer name, manufacturer address.

30

At steps 90, 92, respectively, the injection layer 50 carries out optional checks of order status and current worklist priority. Examples of order status and worklist priority checks include:

- API specific checks.
- Active Order Status, such as:

5 APPOINTMENT_CONFIRMED
 APPOINTMENT_BOOKED
 ARRIVED
 DISCONTINUED
 SCAN_STARTED
 SCAN_COMPLETED
 IMAGES_VERIFIED
10 INTERPRETATION_COMPLETE
 COMPLETE

At step 94, the injection layer 50 communicates the data to predicted radiological findings together with the assigned clinical ranking data to the RIAS 110. At step 96, the RIAS 110 forwards this data to an interactive viewer component 701, which
15 communicates the assigned clinical ranking data to the user at step 98.

The modular components make it highly configurable by users and radiologists in contrast to prior art systems which are rigid and inflexible and cannot be optimised for changes in disease prevalence and care settings. Another benefit of a modular
20 systems architecture comprising asynchronous microservices is that it enables better re-usability, workload handling, and easier debugging processes (the separate modules are easier to test, implement or design). Moreover, the modular aspects allow for users to build an external interface including injection layers/APIs 50, 55. In this way, the system 10 provides an interface specification that allows external applications
25 (patient worklists) to communicate with the system 10 and receive the predicted radiological findings in a more efficient and safe manner, including the order of priority information.

The system 10 also comprises modular components which enable multiple integration
30 and injection pathways to facilitate interoperability and deployment in various existing computing environments such as Radiology Information Systems Picture Archiving and Communication System (RIS-PACS) systems from various vendors and at different integration points such as via APIs 50, 55 or superimposing a virtual user interface element on the display device of the radiology terminals/workstations. The
35 virtual user interface element may be the interactive viewer component 701.

The system 10 provides a plurality of integration pathways via modular subcomponents including: PACS injection, RIS injections, the synchronised viewer component 701, PACS inline frame (iFrame) support, PACS Native AI Support, or a Uniform Resource Locator (URL) hyperlink that re-directs the user to a web viewer on a web page
5 executed in a web browser.

Integration Layer 702 configuration

The integration layer 702 comprising integrator services of an integration adapter,
10 comprises one or more software components that may execute at on-premises hardware. The transmission may be processed, controlled and managed by the integration layer 702 for example installed at the radiological clinic or its data centre, or residing at cloud infrastructure. The integration layer 702 may include a library module containing integration connectors, each corresponding to an integration
15 pathway.

Depending on the PACS system that is used by a customer, the library module may receive a request for a particular integration connector for the system 10 of the present invention to interact with the customer via the PACS system. Advantageously, the
20 library module may receive a request for a particular integration connector for the system 10 of the present invention to interact with the customer via the customer's RIS system, for triage injection for re-prioritisation of studies.

Advantageously, the data may be processed within less than 60 seconds from the
25 integration layer 702 receiving the predicted radiological findings for a study, the message being returned to the RIAS 110/PACS.

The integration layer 702 can store patient data in a database 792a, 792b; for example using local meta data cache to store patient data, which may be enabled or disabled.
30 This increases security and safety aspects of the system 10 when it is not desirable to send patient data to the server system 70 or query patient data. Patient data may include patient ID, patient name, data of both, etc. In preferred embodiments, the time data is stored (retention time) is configurable to increase security aspect of the system 10. The integration layer 702 may be configured so that its functionality is time based

triggered, wherein a time threshold is a configurable parameter. Alternatively, the RIAS may cause the triggering. The time based triggering allows the integration layer 702 to send a message indicating the study is complete (study complete order) to the receiving server 70 if more than a predetermined number of x seconds have elapsed since the last predicted radiological finding (e.g. a radiological image) has been received for the study. In an example x is 15 seconds; preferably, parameter x is configurable. If another predicted radiological finding (i.e. another radiological image) is received after the study complete message is sent to the receiving server 70, parameter x is reset.

10

In preferred embodiments, the integration layer 702 can communicate a JSON payload to HTTP/HTTPS servers. This may be a native integration with the RIAS or by use of an injection layer 50, e.g. MIRTH™ module which represents an integration engine located between the integration layer 702 and the RIAS 110 which functions to reorganise the payload, enabling more robust and secure communication with the RIAS 110. The JSON payload with enhanced information can then be processed by the injection layer 50 to communicate the data in a manner processable by the RIAS 110. Preferably the JSON payload includes data that enables extensibility, that is the JSON payload can be customised. Example API specifications are included in Table 2.

20

Access authentication can be used to allow communication between the processing module 800 and the gateway service 704 of the receiving server 70. These credentials would be requested during the installation through the provisioner tool. Example configurations of the processing module 800 are included in Table 3.

The assign response for each enabled predicted radiological finding is configurable to enable a flexible system for different worklist providers (RIAS 110/PACS). Preferably, the configuration allows, per predicted radiological finding, the worklist fields and values to be set when the finding is present, i.e. a 'Priority' field where the response for a detected pneumothorax (one type of chest radiological finding) is set to Critical.

30

When receiving a DICOM message from the PACS services 65 (step 59), if an assign enabled finding is present in an AI study, the integration layer 702 can update the study

worklist priority according to the assign-enabled finding. The study worklist priority is updated when an assign enabled finding is present in the AI study, or if there are more than one assign enabled finding, the highest ranking response (as defined by the customer) is returned.

5

Retry mechanism

The integration layer 702 may comprise a reiteration mechanism referred to as a “retry mechanism” when it is unable to send (at step 58) the image upload request 60 payload to the server 70 or when it is unable to send the JSON payload to injection layer 50,55 (at step 56, 86; optionally a HTTP response is received from the database 792b). This provides for a more robust and reliable system.

For example, the retry mechanism for non-network related errors may be 1+n and consist of:

1. The integration layer 702 shall retry immediately after first time failure.
- 15 2. On subsequent failures, the integrator shall retry after x seconds delay for n times. For example, default values may be x=10 seconds and n=3 times. Both x and n values are configurable.
3. If the image upload request has exhausted the retry mechanism, then the payload is put onto the dead letter queue.
- 20 4. If the Study Complete has exhausted the retry mechanism, then the payload is put onto the dead letter queue.

For network related errors, the integration layer 702 may retry until successful post can be made for image upload request. For network related errors, the integration layer 702 may retry until successful post can be made for Study Complete upload request. It will be appreciated that the life of messages and queue size of dead letter queue may be configurable to enable flexibility. Examples of network related errors are, internet connectivity issues, server 70 is down and its microservices cannot be accessed (e.g. wrong endpoint URL). Examples of non-network related errors are http 500 ,502, 503, 504, 418, 420, and 429.

30 Injection Layer 50 configuration

Injection layer 50 is a MIRTH™ module which functions to process the JSON payload, converting data from a JSON format to HL7 format. The HL7 standard includes a field that allows for clinical priority to be stored/assigned. This enables the RIAS 110 to receive the predicted radiological findings and associated clinical ranking in HL7 message format to automatically communicate the studies in their priority order (rank) of e.g. Critical, Urgent, and Standard, enabling the RIAS 110 to process and communicate the predicted radiological findings in a more robust and reliable manner. Examples of envisage configurations for the injection layer 50 are included in Table 1.

10

Server systems and methods

With reference to Figure 3, a microservice is responsible for acquiring data from the integration layer 702 to send the CXR images to the AI model 718 for generating predicted radiological findings and then sending back the prioritised predicted findings to the integration layer 702. The microservice is also responsible for storing study-related information, CXR images and predicted radiological findings. The microservice provides various secure HTTP endpoints for the integration layer 702 and the viewer component 701 to extract study information to fulfil their respective purposes.

20

A gateway service 704 provides a stable, versioned, and backward compatible interface to the viewer component 701 and the integration layer 702, e.g. a JSON interface. The gateway 704 provides monitoring and security control, and functions as the entry point for all interactions with a microservice for communicating with an AI model service 718 within the server system 70.

25

The exemplary method of Figure 3 is triggered by a study prediction request being sent by the integration layer 702 to the gateway 704. In particular, at step 780 the integration layer 702 sends a "study predict" request comprising an entire study, and which may include associated metadata, i.e. scan, series and CXR images. The request is received by the gateway 704 which, at step 782, forwards the request and other associated data to a distributed message queueing service (DMQS) 710.

30

At step 783, the request is stored in a database, in this example a cloud imaging processing service (CIPS) 706. The primary functions of the CIPS 706 are to: handle image storage; handle image conversion; handle image manipulation; store image references and metadata to studies and predicted radiological findings; handle image
5 type conversions (e.g. JPEG2000 to JPEG) and store the different image types, store segmentation image results from the AI model(s); manipulate segmentation PNGs by adding a transparent layer over black pixels; and provide open API endpoints for the viewer component 701 to request segmentation maps and radiological images (in a compatible image format expected by the viewer component 701).

10

The DMQS 710 accepts incoming HTTP requests and listens on queues for message from the gateway 704 and a model handling service (MHS) 716. The DMQS 710 is configured to pass, at step 784, CXR images to the MHS 716 for the model prediction pipeline. The DMQS 710 may store studies, CXR images, and deep learning
15 predictions into a database managed by a database management service (not shown). The DMQS 710 also manages each study's model findings state and stores the prioritised predicted radiological findings predicted by the AI models, stores errors when they occur in a database, accepts HTTP requests to send study data including model predictions for radiological findings, accepts HTTP requests to send the status
20 of study findings, and forwards CXR images and related metadata to the MHS 716 for processing of the predicted radiological findings.

The MHS 716 is configured to accept DICOM compatible CXR images and metadata from the DMQS 710. The MHS 716 also performs validation, and pre-processing to
25 transform study data into JSON format, which may then be further transformed into a suitable format for efficient communication within the microservice. Then the MHS 716 sends, at step 786 the study data to an AI model service (AIMS) 718 for AI processing, which identifies and returns the predicted radiological findings generated by the deep learning models executed by a machine learning prediction service. The MHS 716 then
30 accepts the predicted radiological findings generated by the deep learning models which are returned via the AIMS 718. The MHS 716 segments (at step 792), validates, and transforms the prioritized predicted radiological findings representing including CXR data together with clinical ranking data predicted by the AI model 718 into JSON

format and returns these, at step, 794, to the DMQS 710. For example, each JSON file returned corresponds to a single patient study.

The DMQS 710 sends, at step 796, the CXR data together with the clinical ranking
5 data predicted by the AI model 718 to a dispatch service module 750 which functions to send the CXR data and clinical ranking data to the integration layer 702. Preferably, the integration layer 702 sits behind a firewall, and the dispatch service module returns the CXR data results together with the predicted clinical ranking, at step 798, via a WebSockets service, thereby providing a security benefit.

10

Systems

With regard to the preceding overview of the system 10, and other processing systems
15 and devices described in this specification, terms such as 'processor', 'computer', and so forth, unless otherwise required by the context, should be understood as referring to a range of possible implementations of devices, apparatus and systems comprising a combination of hardware and software. This includes single-processor and multi-processor devices and apparatus, including portable devices, desktop computers, and
20 various types of server systems, including cooperating hardware and software platforms that may be co-located or distributed. Physical processors may include general purpose CPUs, digital signal processors, GPUs, and/or other hardware devices suitable for efficient execution of required programs and algorithms.

25 Computing systems may include conventional personal computer architectures, or other general-purpose hardware platforms. Software may include open-source and/or commercially available operating system software in combination with various application and service programs. Alternatively, computing or processing platforms may comprise custom hardware and/or software architectures. As previously noted,
30 computing and processing systems may comprise cloud computing platforms, enabling physical hardware resources, including processing and storage, to be allocated dynamically in response to service demands.

Terms such as 'processing unit', 'component', and 'module' are used in this
35 specification to refer to any suitable combination of hardware and software configured

to perform a particular defined task. Such a processing unit, components, or modules may comprise executable code executing at a single location on a single processing device, or may comprise cooperating executable code modules executing in multiple locations and/or on multiple processing devices. Where exemplary embodiments are
5 described herein with reference to one such architecture (e.g. cooperating service components of the cloud computing architecture described above) it will be appreciated that, where appropriate, equivalent functionality may be implemented in other embodiments using alternative architectures.

10 The program code embodied in any of the applications/modules described herein is capable of being individually or collectively distributed as a program product in a variety of different forms. In particular, the program code may be distributed using a computer readable storage medium having computer readable program instructions thereon for causing a processor to carry out aspects of the embodiments of the invention.

15 Computer readable storage media may include volatile and non-volatile, and removable and non-removable, tangible media implemented in any method or technology for storage of information, such as computer-readable instructions, data structures, program modules, or other data. Computer readable storage media may
20 further include random access memory (RAM), read-only memory (ROM), erasable programmable read-only memory (EPROM), electrically erasable programmable read-only memory (EEPROM), flash memory or other solid state memory technology, portable compact disc read-only memory (CD-ROM), or other optical storage, magnetic cassettes, magnetic tape, magnetic disk storage or other magnetic storage
25 devices, or any other medium that can be used to store the desired information and which can be read by a computer. Computer readable program instructions may be downloaded via transitory signals to a computer, another type of programmable data processing apparatus, or another device from a computer readable storage medium or to an external computer or external storage device via a network.

30 Computer readable program instructions stored in a computer readable medium may be used to direct a computer, other types of programmable data processing apparatus, or other devices to function in a particular manner, such that the instructions stored in the computer readable medium produce an article of manufacture including

instructions that implement the functions, acts, and/or operations specified in the flowcharts, sequence diagrams, and/or block diagrams. The computer program instructions may be provided to one or more processors of a general purpose computer, a special purpose computer, or other programmable data processing
5 apparatus to produce a machine, such that the instructions, which execute via the one or more processors, cause a series of computations to be performed to implement the functions, acts, and/or operations specified in the flowcharts, sequence diagrams, and/or block diagrams.

10 Interpretation

Software components embodying features of the invention may be developed using any suitable programming language, development environment, or combinations of languages and development environments, as will be familiar to persons skilled in the
15 art of software engineering. For example, suitable software may be developed using the TypeScript programming language, the Rust programming language, the Go programming language, the Python programming language, the SQL query language, and/or other languages suitable for implementation of applications, including web-based applications, comprising statistical modelling, machine learning, data analysis,
20 data storage and retrieval, and other algorithms. Implementation of embodiments of the invention may be facilitated by the used of available libraries and frameworks, such as TensorFlow or PyTorch for the development, training and deployment of machine learning models using the Python programming language.

25 It will be appreciated by skilled persons that embodiments of the invention involve the preparation of training data, as well as the implementation of software structures and code that are not well-understood, routine, or conventional in the art of anatomical image analysis, and that while pre-existing languages, frameworks, platforms, development environments, and code libraries may assist implementation, they require
30 specific configuration and extensive augmentation (i.e. additional code development) in order to realize various benefits and advantages of the invention and implement the specific structures, processing, computations, and algorithms described herein with reference to the drawings.

The described examples of languages, environments, and code libraries are not intended to be limiting, and it will be appreciated that any convenient languages, libraries, and development systems may be employed, in accordance with system requirements. The descriptions, block diagrams, flowcharts, tables, and so forth, presented in this specification are provided, by way of example, to enable those skilled in the arts of software engineering, statistical modelling, machine learning, and data analysis to understand and appreciate the features, nature, and scope of the invention, and to put one or more embodiments of the invention into effect by implementation of suitable software code using any suitable languages, frameworks, libraries and development systems in accordance with this disclosure without exercise of additional inventive ingenuity.

Any discussion of documents, acts, materials, devices, articles or the like which has been included in the present specification is not to be taken as an admission that any or all of these matters form part of the prior art base or were common general knowledge in the field relevant to the present disclosure as it existed before the priority date of each of the appended claims.

Those skilled in the art will be able to make modifications and alternatives in view of the disclosure which are contemplated as falling within the scope of the appended claims. Each feature disclosed or illustrated in the present specification may be incorporated in the invention, whether alone or in any appropriate combination with any other feature disclosed or illustrated herein.

It will be appreciated that the order of performance of the steps in any of the embodiments in the present description is not essential, unless required by context or otherwise specified. Therefore, most steps may be performed in any order. In addition, any of the embodiments may include more or fewer steps than those disclosed.

Additionally, it will be appreciated that the term “comprising” and its grammatical variants must be interpreted inclusively, unless the context requires otherwise. That is, “comprising” should be interpreted as meaning “including but not limited to”.

Tables**Table 1**

User Integration	Priority Mapping Configuration	Injection Layer 50 Configuration
1. Visage RIS 2. No separate AI priority 3. No ability to display predicted radiological findings	Can provide more than one level of priority e.g. <pre>{ "assignPriorities":[{ "assignPriorityId":0, "rank":1, "priority":"10" // Critical }, { "assignPriorityId":1, "rank":2, "priority":"20" // Urgent }, { "assignPriorityId":1, "rank":3, "priority":"30" // Standard }] }</pre>	1. Pre-check of order status enabled 2. Pre-check of priority status enabled 3. Inject into existing clinical priority status
1. Other HL7 RIAS 2. No separate AI priority 3. No ability to display predicted radiological findings	Can only provide one level of priority. That is the highest level. e.g. <pre>{ "assignPriorities":[{ "assignPriorityId":0, "rank":1, "priority":"10" // Critical }] }</pre>	1. Pre-check of order status disabled 2. Pre-check of priority status disabled 3. Inject into existing clinical priority status

1. Other HL7 RIS 2. Separate AI priority 3. No ability to display predicted radiological findings	Can provide more than one level of priority	1. Inject into AI priority status
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1. Other HL7 RIS 2. Separate AI priority 3. Has ability to display predicted radiological findings	Can provide more than one level of priority	1. Inject into AI priority status 2. Provide the information to injection layer 50 to display findings. e.g. of payload to injection layer 50 <pre>{ "highestPriorityFinding": { "highestPrioritylabel": "oesophageal_stent", "highestPrioritylabelName": "Oesophageal Stent" }, "allAssignFindings": [{ "groupId": 1, "groupName": "Priority", "assignOrder": 1, "findings": [{ "label": "oesophageal_stent", "labelName": "Oesophageal Stent", "displayOrder": 32, "priorityId": 10 }, { "label": "lung_collapse", "labelName": "Lung Collapse", "displayOrder": 64, "priorityId": 10 }] }] }</pre>
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Table 2

POST Request to /priority	Response
Result { "accessionNumber": "71.15282371", "studyInstanceUid": "1.2.6.1.4.1.14301.74.4.14862474.1", "priority": "10", "priorities": [{ "priority": "10", "rank": 1 }, { "priority": "20", "rank": 2 }, { "priority": "30", "rank": 3 }], "patient": { "patientId": "71.5736122", "patientName": "John Doe", "patientDob": "19860916", "patientSex": "M" }, }	Initially response could indicate: 200 OK: Worklist has been updated with the new priority list or found possible precheck errors: • Study deleted / not found / completed • Priority of the study is already higher (currently used in ris-injector): { priorityUpdated, //boolean, mandatory worklistPriority, //string, optional worklistStatus, //string, optional error //string, optional }

<pre>productDetails:{ "productName":"Annalise CXR" "softwareVersion":"2.0.0-003", "UDI":"Null", "manufactureName":"Annalise-AI Pty Ltd", "manufacturerAddress":"Level 5, 24 York Street, Sydney, NSW, 2000, Australia" }</pre> • productName = hardcoded as Annalise CXR • softwareVersion = get from the receiving server 70 • UDI = hardcoded as Null • manufactureName = hardcoded as Annalise-AI Pty Ltd • manufacturerAddress = hardcoded as Level 5, 24 York Street, Sydney, NSW, 2000, Australia	
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<pre> "highestPriorityFinding":{ "finding":"Oesophageal Stent", "priority": "10" }, "allAssignFindings":[{ "group":"Priority", "assignOrder":1, "findings":[{ "finding": "Oesophageal Stent", "priority":"10" }, { "finding":"Lung Collapse", "priority":"20" }] 43 }, { "group":"Other", "assignOrder":2, "findings":[{ "finding":"Rib Resection", "priority": "20"}, { "finding":"Shoulder Arthritis", "priority":"30"}] }], </pre> Update Results processor to generate the following as part of the payload to the injection layer 50: 1. Highest priority finding. Note: if there are multiple priorities with the same rank, then use display priority to determine the highest. 2. All relevant findings. 3. Based on the new payload. The injection layer 50 will also be able to determine all relevant findings that is in the high priority group. i.e based on assignOrder.	
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Table 3

New env variable	Type	Default value?
Add product details	bool	false
add findings	bool	false
ris_auth_username	string	None
ris_auth_password	string	None

CLAIMS

1. A method comprising the steps of:
 - providing a plurality of visual findings in one or more anatomical images of a subject, wherein the plurality of visual findings are generated using a convolutional neural network, CNN, component of a neural network, wherein a subset of the generated visual findings represents a set of priority findings; providing a first classification list for the plurality of visual findings, to associate a first clinical ranking to the set of priority findings, respectively;
 - providing a second classification list wherein the second classification list is user configurable;
 - assigning a clinical ranking to the set of priority findings, respectively, using at least one of the first and second classification lists;
 - combining the set of priority findings and their respectively assigned clinical ranking to form triage data; and
 - communicating the triage data to a user system configured to process the triage data and to generate, using the triage data, an output that represents a re-ordered worklist.
2. A method according to claim 1, wherein the second classification list takes precedence over the first classification list.
3. A method according to claim 1 or claim 2, wherein the clinical ranking is assigned using both the first and second classification lists, assigning the clinical ranking comprises the steps of: obtaining a first ranking value for a priority finding using the first classification list, obtaining a second ranking value for said priority finding using the second classification list, and providing the second ranking value as the assigned clinical ranking only if the second ranking value is equal to or higher than the first ranking value.
4. A method according to any one of the preceding claims, wherein the triage data comprises an indication of priority findings from the plurality of priority findings that correspond to only one of the group of:

said priority findings, priority findings that have been assigned a clinical value, a priority finding that has been assigned a highest clinical ranking.

5. A method according to any one of the preceding claims, wherein the method
5 further comprises the step of: using the triage data to update a user's worklist corresponding to the plurality of visual findings.
6. A method according to claim 5, wherein updating the user's worklist is
10 configurable to use only one of the group of: said priority findings, priority findings that have been assigned a clinical value, a priority finding that has been assigned a highest clinical ranking.
7. A method according to any one of the preceding claims, wherein the triage data
15 is provided in a JavaScript Object Notation, JSON, format.
8. A method according to claim 7, wherein communicating the triage data
comprises converting the triage data to a Health Level 7, HL7 format.
9. A method according to any one of the preceding claims, wherein the plurality of
20 visual findings and associated first clinical ranking are provided by a server module to an integration layer module.
10. A method according to claim 9, wherein the visual findings and associated first
25 clinical ranking are provided using a WebSockets protocol.
11. A method according to any one of the preceding claims, wherein the integration
layer module comprises a database for storing the triage data for a period of
time which is configurable by the user.
- 30 12. A system for transmitting triage data for a plurality of visual findings in one or
more anatomical images of a subject, wherein the plurality of visual findings are
generated using a convolutional neural network, CNN, component of a neural
network, the system comprising: at least one processor; and at least one
computer readable storage medium, accessible by the processor, comprising

instructions that, when executed by the processor, cause the processor to execute a method according to any one of the preceding claims.

- 5 13. A non-transitory computer readable storage media comprising instructions that, when executed by at least one processor, cause the processor to execute a method according to any one of the preceding claims.