# Artificial Intelligence Applications for Workflow, Process Optimization and Predictive Analytics

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## KEYWORDS

• Artificial intelligence • Machine learning • Workflow • Decision support • Smart device • Radiology • Medical imaging • Operational efficiency

## KEY POINTS

- In addition to the use of artificial intelligence (AI) for medical image analysis for diagnostic classification and interpretation tasks, there are many additional important applications as it pertains to workflow optimization and support for interpretation tasks, quality and safety, and operational efficiency.
- Successful implementation of AI workflow applications are contingent on a robust and integrated informatics infrastructure.
- Process and workflow optimization applications of AI in health care may be easier to achieve in the near term both from a technical standpoint and from the perspective of other barriers, such as regulatory barriers and user acceptance and adoption.

## INTRODUCTION

Applications of artificial intelligence (AI) in health care, especially machine learning, have garnered significant attention in the last decade. In radiology, advances in machine learning approaches, especially the development of deep learning, coupled with tremendous increases in computational processing power, have

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revolutionized computerized medical image analysis.[1–4] There is great potential in the application of machine learning for image analysis diagnostic decision support tasks and precision medicine.[5,6] Many are discussed in detail in multiple accompanying articles in this issue. However, the potential applications of AI in radiology go beyond image analysis tasks such as lesion classification or segmentation alone. AI has the potential to enhance all levels of the radiology workflow and practice, including workflow optimization and support for interpretation tasks, quality and safety, and operational efficiency (**Box 1**, **Fig. 1**). This article reviews these important potential applications of informatics and AI related to process improvement and operations in the radiology department. This article focuses on the potential additive value of AI, but before discussing the different applications, it is important to keep the following fundamental principles in mind. For the different applications, any successful implementation of AI in the radiology department or the broader health care system is contingent on a robust informatics network. Furthermore, AI applications are a supplement to other important informatics tools and software that do not constitute AI. Therefore, even though not explicitly mentioned or repeated in this article, this important and fundamental principle applies to all of the applications described.

## NATURAL LANGUAGE PROCESSING

There has been much attention paid to machine learning applications for image analysis but this should not detract from the importance of natural language processing (NLP) for developing applications and tools that enhance radiology practice. Because of the importance of NLP for many of the potential applications discussed in this article, a brief review is provided of NLP before proceeding to a discussion of specific AI applications for process and workflow optimization. A historical discussion of the evolution of NLP is beyond the scope of this article but, for current practical purposes, NLP can be considered as a specific subfield of AI that converts narrative text into structured data.[7] NLP can be used to process unstructured text data from requisitions (ie, clinical and demographic information) and render it interpretable to computers and algorithms. Once the raw text is transformed into structured data, a final step involves vectorization. Because algorithms only understand numerical representation as their inputs, vectorization transforms words into vector form.

Traditional NLP techniques normally represent every word as a 1-hot encoded one-dimensional vector.[7–11] That is, every word found in the vocabulary of the dataset will be represented by a single unique binary vector. From this, it is possible to represent an entire document using a bag-of-words vectoral approach (**Fig. 2**), which in turn allows the creation of a term frequency–inverse document frequency (TF-IDF) matrix.[8–12] TF-IDF matrices are a popular approach to text representation because they emphasize the less common words in the corpus that may carry more predictive value.[10] However, there are many drawbacks to using this form of vector representation, including loss of word context (ie, similar medical terms have independent binary representations) and creation of very sparse vectors.[7] This high vector space can become problematic and reduce classification optimization by overfitting the dataset.[12] More recent techniques incorporating deep learning implement word embedding, allowing word context preservation and dimension reduction; common models used for this purpose include Word2vec and Glove.[7,13] Pretrained models are available but training a personalized model on a corpus related to the medical domain field may be more advisable.

Similar to other machine learning algorithms, an NLP classifier's performance is greatly dependent on the quality of its dataset, an important feature being its size. Spasic and Nenadic[14] (2020) showed in their systematic review that most datasets used to train machine learning NLP algorithms in the clinical health care setting are only hundreds or thousands of documents in length. In the few studies pertaining to radiology protocol selection, dataset size roughly ranged from 6700 to 18,000 documents.[8–11,13] One reason for these small sizes is the annotation bottleneck effect commonly afflicting supervised machine learning models.[14] For example, for creating an automated protocoling engine using supervised machine learning, selection requires input data coupled with an output class from a predefined set of standard protocols.[8–11,13] Generating standard protocols from free-text ones and manually annotating them to the dataset can be strenuous and time consuming. When standard protocols are not readily available in an institution's electronic health record (EHR), semiautomatic techniques with manual verification are one possible approach used to convert free-text protocols to a defined standard form.[11,13] String searching algorithms such as regular expressions are some examples sought out to find and replace such protocols. Other approaches proposed to facilitate protocol annotation yet to be tested include active learning (**Fig. 3**) and unsupervised learning methods (ie, K-clustering and hierarchical clustering); however, the efficiency of these techniques depends on the algorithm's

**Box 1**
**Potential applications of machine learning in radiology**

Before imaging examinations or procedures

- Clinical decision support[a]
- Patient scheduling and screening
- Protocoling

During imaging examinations or procedures

- Image acquisition
- Image optimization (eg, motion artifact, noise reduction)
- Image generation (eg, low-dose gadolinium,[32] synthetic MR imaging)
- Supplementary magnetic resonance (MR) imaging sequence suggestions based on findings

After imaging examinations or procedures (before interpretation)

- Automated radiation dose estimation
- Image postprocessing (reformations, segmentations, quantifications)
- Advanced image analysis, including radiomics and delta-radiomics extraction
- DICOM routing and workflow orchestration
- Worklist prioritization
- Preliminary interpretation
- Pre-dictation

After imaging examinations or procedures (during interpretation)

- Contextual report template recommendation
- Assisted segmentations
- Electronic medical record extraction and correlation with other relevant data for interpretation
- Prognostic inference
- Quality (including peer review) and safety

After interpretation

- Urgent finding notification
- International Classification of Diseases (ICD) code extraction from report
- Billing
- Compliance
- Abuse and fraud detection (insurer or Medicare level)

[a]Clinical decision support for ordering of radiology scans discussed here should not be confused with the more generic use of the term in the radiomics and machine learning literature discussing the use of image analysis with radiomics and AI for diagnostic decision support, alluding to diagnostic information extracted from imaging studies[16] for augmenting the expert radiologist's final interpretation.

*Adapted from* Choy.[4]

capability to correctly classify and annotate the free-text protocol, which could result in long retraining time cycles if not optimal.[14]

In addition, 2 important performance metrics are commonly calculated in text classification: precision and recall.[12] Precision is defined as the probability that a given document (eg, a computed tomography [CT] requisition) classified under a given category (ie, a standard protocol) is correct.[12] Precision grossly correlates to positive predictive value. Recall is defined as the probability that, if a random document should be classified under a given category, this decision be correctly taken by the classifier.[12]

$$precision = \frac{tp}{tp+fp} \quad recall = \frac{tp}{tp+fn}$$

where $tp$ = true positives, $fp$ = false positives, $fn$ = false negatives.

Two approaches from which different inferences can be formulated are used to calculate precision and recall. Macroaveraging initially calculates the classifier's precision and recall for each category, and the mean of these scores is then calculated.[12] This approach highlights how well a classifier does with regard to categories having smaller samples. Analogously, weighted precision and recall account for category imbalance by assigning a weight to every score according to the category's distribution in the dataset. Weighted recall is commonly referred as a classifier's accuracy. A combined metric such as the F-measure is usually compiled; the F-measure is a harmonic mean of precision and recall and reaches its best values as it approaches the value of 1.[12] Moreover, other metrics, such as inter-radiologist discordance measurements, may provide additional insight on potential sources of model error.[10]

When developing NLP applications, it is important to understand the strengths and pitfalls in algorithm development in order to develop robust and reliable applications. With this brief overview of NLP, this article next discusses different AI applications, using machine learning and NLP, for process and workflow improvement in the radiology department. More in-depth reviews of NLP, different machine learning approaches, and approaches for the evaluation of machine learning algorithms are provided elsewhere in this issue.

## PRE-IMAGE ACQUISITION WORKFLOW ENHANCEMENT: SCAN ORDERING, PROTOCOLING, AND SCHEDULING

### *Scan Ordering and Clinical Decision Support Tools*

There has been significant interest in imaging and the use of clinical decision support software to

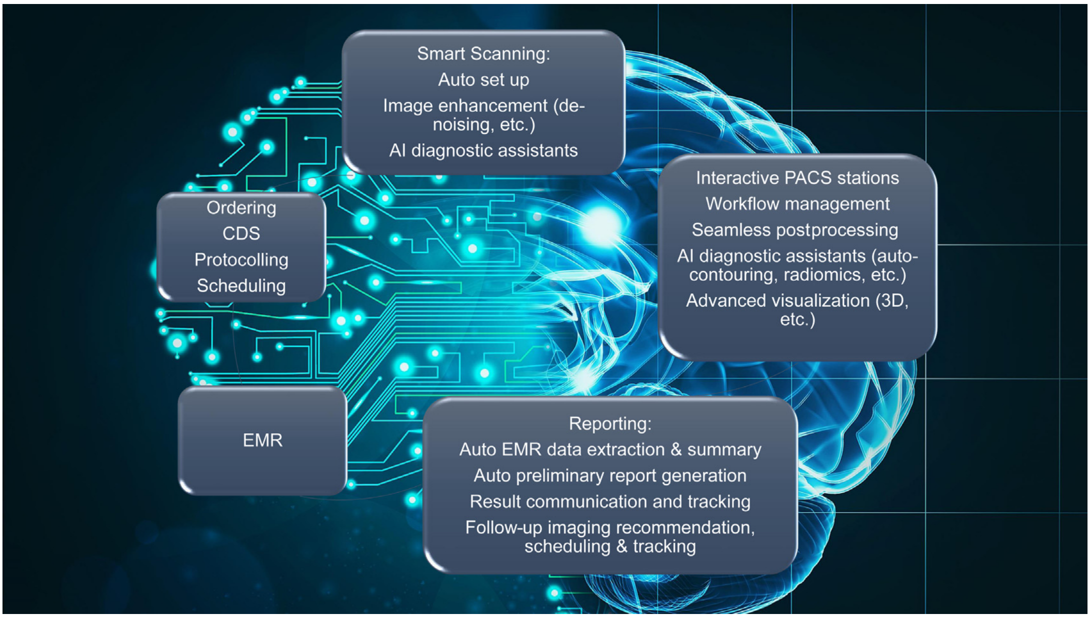


**Fig. 1.** There are many potential applications of AI, more specifically machine learning and natural language processing, in the radiology department. In addition to important augmented diagnostic assistant tools for precision medicine, many other important applications are process and workflow related. This figure provides an example of some of these applications relevant to different processes and workflow in the radiology department. CDS, clinical decision support; EMR, electronic medical record; 3D, three-dimensional.

optimize the process of radiology scan ordering and reduce ordering of unnecessary scans over the past 2 decades.[15–17] For greater clarity, the clinical decision support for ordering of radiology scans discussed here should not be confused with the more generic use of the term in the radiomics and machine learning literature discussing the use of image analysis with radiomics and AI for diagnostic decision support (see **Box 1**), alluding to diagnostic information extracted from imaging studies for enhancing or augmenting the expert radiologist's final interpretation.[6,18] Preliminary studies suggesting that AI-based frameworks may be able to perform robustly and approximate the human decision-making process in complex and uncertain environments suggests that AI engines supporting traditional clinical decision support software have great potential for optimizing scan ordering, reducing wasteful use or erroneous scan ordering and protocoling, and improving overall patient care.[4,17,19] Automated retrieval of clinical data from the EHR can even be envisioned, improving the quality and efficiency of clinical decision support software in the future.[20]

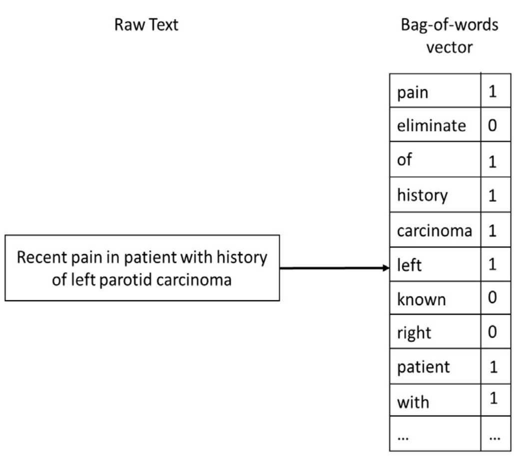


**Fig. 2.** Example of text vectorization based on a bag-of-words model.

## *Patient Screening, Scan Protocoling, and Scheduling*

Scan protocoling and scheduling are discussed together because, in the radiology department, these are inevitably intertwined. Efficient and streamlined scheduling of radiology examinations poses unique administrative and operational challenges because the proper scheduling of scans is contingent on specific medical information. This situation can pose a challenge for administrative personnel with no formal medical background. The typical process where the input from an expert radiologist and/or radiology technologist is required in the chain of mainly administrative tasks

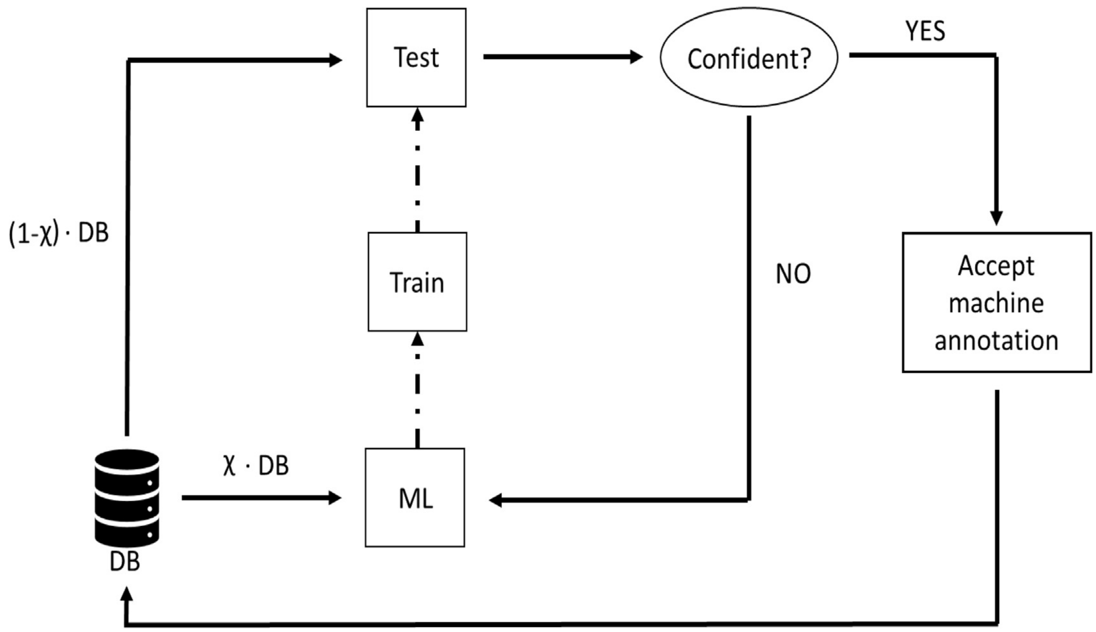


Fig. 3. Active learning tackles the annotation bottleneck phenomenon allowing much less annotation effort.[14] This method requires a professional to manually label a sample of the free-text protocol dataset and then iteratively train a machine learning algorithm over it in order to predict the annotation of the remaining dataset. Measures of uncertainty, probability, and/or density can be used to guide the algorithm's confidence level; when the algorithm is uncertain about its annotation for a given input, the expert can manually label the free-text protocol. The newly labeled input is then reinserted and the algorithm retrained with the modified dataset. This process is done until it can annotate the standard protocol of the whole dataset with a high confidence level. $\chi$ is the predefined ratio of the database that will be used for manual labeling (ML). DB, database containing free-text protocols.

creates undesirable inefficiencies, which can be disruptive for the administrative personnel, radiologists, and patients in providing a streamlined and efficient service.

A well-structured informatics system with the support of AI has great potential in streamlining this process (see **Box 1**).[21] With increasing sophistication of NLP and machine learning applications, there is the possibility of efficient safety screening of patients before scheduling a scan, identifying contraindications or creatinine when required for scheduling of a contrast-enhanced study. This screening has the potential concurrently improve patient safety and operational efficiency.

Scan protocoling is a time-consuming and repetitive task and can take up a considerable portion of a radiologist's time.[22] Moreover, the accumulation of requisitions to be protocoled can contribute to outpatient imaging wait times. Although computerized clinical decision support systems using machine learning techniques are increasingly popular, few have studied their applicability for protocoling. Constructing support systems for automated protocol selection initially involves using NLP techniques to extract and process pertinent clinical text data from the clinical indication/history field and from prior imaging reports and build a training dataset. Subsequently annotating this training dataset with predefined standard protocols then allows for text classification using supervised learning algorithms. Common techniques used to process raw text in studies of automated protocol selection include conversion to lowercase, removal of stop words (ie, words with little predictive value such as "and," "or," "the," "please"), removal of punctuation and numerical values, tokenization, lemmatization, and stemming.[8–10]

Algorithms used in studies of imaging protocol automation have included support vector machine, gradient boosting machine, random forest, and K-nearest neighbor.[8–11] These studies have shown promising results.[8–10] These models can all be tagged as traditional NLP techniques or shallow learning models that require a process called feature selection (ie, input variable selection) before they can start training on the dataset. Common features (or variables) that were used as input to the learning models included clinical indication and history (processed via NLP techniques as stated earlier), patient demographics (age and sex), and ordering service.[8–10,13] However, a greater role is now to be expected from emerging deep learning methods based on their performance for other NLP tasks.[7] These methods include a broad range of classifiers, ranging from convolutional neural networks (CNNs) to recurrent neural networks and long short-term memory. These new methods have the advantage of not requiring human involvement in feature selection; the computer automatically emphasizes features that have more predictive impact while in training.[7] Two studies of CNNs for musculoskeletal image protocoling, Trivedi and colleagues[11] (2018) and Lee[13] (2018), have shown promising results for automatic determination of intravenous contrast administration and tumor versus routine protocol selection (accuracy of 80% and 94% respectively). More recently, Kalra and colleagues[10] (2020) showed the effectiveness of a deep neural network for CT and magnetic resonance (MR) imaging protocol selection, reaching 95% accuracy for the assignment of 69% of their protocols where optimal confidence thresholds were met and 92% accuracy for the remaining 31% by providing a top-3 protocol suggestion for clinical review.

Successful implementation of a semiautomatic or automatic protocoling engine can significantly improve and enhance the administrative and scheduling processes in the radiology department, and free up the radiologists for more important, higher-level activities. By automating this process and taking the radiologist out of this mainly administrative loop, much more streamlined scheduling is possible where most scans are automatically protocoled based on the information provided in the requisition and/or the information in the EHR. In this scenario, only a small percentage of ambiguous requests or complex cases may be flagged for review and protocoling by the radiologist. In robust and properly set up systems, it may eventually even be possible to support live interactive booking by the patient in most cases, which would improve patient satisfaction in addition to operational efficiency.

Beyond the simple but important operational impact of automation of most protocoling-scheduling tasks, in the future, AI applications can be foreseen that could improve the process beyond what is currently done. In most radiology departments, the selection of a scan protocol is done based on limited information provided in the requisition. It is not practically feasible to consult and evaluate in detail every patient's chart when performing protocoling tasks, which introduces certain important deficiencies and inaccuracies in the process. Moreover, for follow-up studies, the optimal timeline for follow-up relative to the prior examination may not be evident unless specified by the ordering physician. In the future, robust well-structured informatics systems combined with NLP are likely to overcome these challenges based on the analysis of the patient's electronic medical record and even automated selection of the scan time and optimal scan type. These systems may alert the referring physician and/or radiology department when a recommended follow-up was not scheduled, provided yet another level of quality control and safety measures in the system. Furthermore, such systems may identify redundant scans or poorly timed follow-up scans (eg, a prematurely booked follow-up scan), providing an opportunity for the referring physician and/or radiologist to be alerted in order to rectify the situation. These future applications of AI are important potential and likely feasible as proper health informatics infrastructures are developed and optimized.

## ARTIFICIAL INTELLIGENCE AI APPLICATIONS DURING IMAGE ACQUISITION: SMART DEVICES

AI has great potential for improving the radiology scan acquisition process, including as assistive technology for improving radiology technologists and enabling increased scan quality and acquisition efficiency (see **Box 1**).[4] As an example, in MR imaging there is potential for AI-supported guidance and assistance in patient positioning, or matching of sequences with prior studies when appropriate. AI-supported engines may also identify outliers or cases where additional sequences may be required based on a patient's past scans. All of these steps can improve quality at the acquisition, providing important assistive support to the imaging technologist. In CT, AI not only has the potential to assist in patient positioning but also can optimize CT dose. As an example, rather than picking categories such as small, medium, or large for radiation dose modulation, AI has the potential to truly personalize radiation dose to a patient's body habitus based on the scout view that has been obtained.[23] In cases where there are metallic implants or other sources of artifact, appropriate automated processes can be preprogramed that would enable optimal acquisition and generation of additional reconstructions. For example, in the neck, detection of dental material on the scout view could automatically prompt the need for the acquisition of an angled gantry or open-mouth view (depending on a specific scanner and practice). Metal prostheses could also automatically trigger reconstruction using a metal artifact reduction algorithm. This possibility has the potential to standardize and enhance the quality of the examinations at acquisition, performing this efficiently and enabling both quality improvement and streamlining of operational processes. The scans could even be preprogramed to automatically detect quality deficits prompting repeat scans when appropriate (eg, extreme motion) in either MR imaging or CT with automated application of necessary interventions. These developments hold great potential for AI in the future in streamlining the scanning process.

In addition to the possibilities discussed earlier, there are potential applications of machine learning for image reconstruction in CT, MR imaging, or other modalities in order to improve image quality and/or operational efficiency (see **Box 1**). In CT, other than the patient-tailored dose estimation discussed earlier, deep learning–based reconstruction approaches can be used for noise reduction and radiation dose optimization.[24–27] In MR imaging, deep learning similarly can be used to enhance the image acquisition process by improving general image quality, performing motion correction, and reducing sequence acquisition time, resulting in improved operational efficiency.[28–31] Most of these manipulations are performed on the raw data, but certain deep learning–based manipulations and improvements can also be done in the image space after scan acquisition. There are also potentially more advanced applications of deep learning. These applications include real-time image analysis to recommend modifications to sequences or addition of other sequences to a scan.[4] They also include applications for reducing contrast agent dose or generation of various synthetic images.[32–36]

## POST–IMAGE ACQUISITION WORKFLOW ENHANCEMENT: BEFORE AND DURING IMAGE INTERPRETATION

### *DICOM Image Routing, Workflow Orchestration, and Image Postprocessing*

Another area where a properly set up informatic system with AI can be of great help would be more efficient and optimal workflow orchestration and DICOM image routing (see **Box 1**). AI has the potential to enhance existing informatic solutions for end-to-end workflow, image management, and analytics, including creation of intelligent worklists harmonizing and optimizing case assignment and workflow within the department at 1 hospital or across different hospital or clinic sites. Thereafter, an example of the use of AI for improving workflow efficiency is automatic creation of hanging protocols.[37,38] Although this may seem simplistic, having optimal hanging protocols with proper fetching and matching of prior studies is difficult to achieve based on DICOM metadata alone. Using AI engines with additional image analytical capabilities, this can be enhanced, resulting in overall improvement of productivity. Pertaining to image processing, the applications of AI are numerous, ranging from generating various reconstructions to complex image processing and analytical tasks, including feature extraction and radiomics. A discussion of these is beyond the scope of this article but can be found in accompanying articles in this issue or different reviews on the topic.[4–6,18]

### *Radiology Worklist Prioritization: Prioritization of Critical Findings*

At present, a widely used application of AI for workflow is reading list prioritization (see **Box 1**). In this scenario, images are analyzed and those with potential critical findings are flagged and pushed to the top of the list for more immediate reading. This application can improve turnarounds for examinations with critical findings where time could be of the essence for patient management. In health systems where there are large backlogs, such engines also have the potential to flag and enable a more rapid read of examinations that could be abnormal.

Detection of urgent actionable findings on imaging study is important to prevent patient morbidity and mortality as well as to mitigate medicolegal risks. It is identified as an important goal by the Joint Commission in their National Patient Safety Goal.[39] The American College of Radiology recommends nonroutine communication of “findings that suggest a need for immediate or urgent intervention.”[40] A secondary benefit of rapid detection of such findings is increased productivity gained from the reduction of interruptions related to inquiries about urgent reports.

To accelerate the identification of such findings, most radiology practices use a worklist prioritization strategy. The most basic implementation is through a rule-based system, such as filters already available within picture archiving and communication systems (PACS). These rules can consider, for example, the patient's location for inpatients (eg, emergency room or intensive care unit) or examination priority for outpatients. So-called stat creep can hamper the implementation of such strategies over time.[41,42] Alternatives include server-based enterprise collaboration software [43] or EHR-driven solutions,[41] which allow increased granularity and efficiency compared with PACS-based strategies. Several companies offer worklist prioritization software with PACS integration. A major drawback of these non–AI-based strategies is that they may not be able to properly prioritize scans with potential unexpected critical findings.

Contrary to these prioritization strategies, machine learning–driven worklist prioritization typically uses the information available within the images. Among critical findings, intracranial hemorrhage is frequently cited as the most important to detect rapidly.[44,45] The 2019 RSNA AI challenge was aimed at detection and classification of acute intracranial hemorrhage (https://www.kaggle.com/c/rsna-intracranial-hemorrhage-detection). Algorithms used for such tasks are typically image classifiers and can detect critical findings such as hemorrhage,[46] mass effect, midline shift,[47,48] hydrocephalus, acute ischemic stroke, large vessel occlusion,[49] or a combination of these conditions[44,50] before formal reading, allowing rapid notification of radiologists and worklist prioritization.

Diagnostic performance of such implementations are variable and depend notably on the type of model and dataset used for training the algorithm. Prevedello and colleagues[44] built a deep learning algorithm to detect hemorrhage, mass effect, and hydrocephalus with 90% sensitivity and 85% specificity. Similar to human performance, a separate algorithm dedicated to the identification of suspected acute infarct, which is generally more difficult to detect than hemorrhages, had lower accuracy, with 62% sensitivity and 96% specificity.[44] Chilamkurthy and colleagues[50] used a much larger dataset to identify different types of intracranial hemorrhages, calvarial fracture, mass effect, and midline shift. Using high-sensitivity operating points, the sensitivity for these findings on different test datasets was between 90% and 95% and specificity between 60% and 88% depending on the finding. Non-CNS or head and neck findings, such as the identification of pneumothorax, could also be integrated in such critical finding detection models.[51] Finally, in addition to critical findings, the identification of common incidental findings on head and neck studies, such as pulmonary[52] or thyroid nodules,[53] can also be performed.

## Preliminary Radiology Report Generation

One possible extension and more advanced application of preliminary automated image analysis, such as that used for worklist prioritization, could be a more sophisticated diagnostic support (such as the example provided earlier for incidental findings). However, another application by linking to NLP is the generation of preliminary reports (see **Box 1**). Interpretation of radiology examinations requires high-level expertise and adaptation to the appropriate clinical scenario.[4,54] A recent study combining deep learning and bayesian networks, mimicking perceptual and cognitive tasks performed by radiologists, was able to infer differential diagnoses approaching the accuracy of neuroradiologists and surpassing trainees' performance.[55] In this study, the addition of clinical features added significant diagnostic accuracy to the model. This task was aimed at a particular entity (fluid-attenuated inversion recovery hyperintensities on brain imaging) and remains limited in scope but shows the potential of such technology to augment interpretation of imaging.

Automatic radiology report generation is another complex task that must integrate accurate analysis of medical images with appropriate natural language description. This ability has been leveraged by advances in computer vision and language translation.[56,57] The first study specifically aimed at radiology reports was described by Shin and colleagues in 2016.[57] Earlier research on this topic was based on image captioning, which is a simpler task compared with the generation of full radiology reports.[56–58]

A typical approach to tackle this problem is to combine a CNN for image detection and classification with a recurrent neural network for text generation.[57,58] In particular, recurrent neural network encoder-decoder architectures with long short-term memory typically used in language translation have been used to generate complete sentences.[57,58] Furthermore, generation of long sentences and paragraphs, such as in the findings section of a radiology report, is a task that requires hierarchical neural networks.[58,59] So far, most studies have focused on the interpretation of chest radiographs using a publicly available dataset of limited size (the Indiana University Chest X-ray Collection).[60] Different approaches have been used, often mimicking the radiologist's perceptual and cognitive tasks.[56,58,59] Interpretability of such models can be enhanced by the use of attention maps.[56,59] In the model built by Yuan and colleagues,[59] activation maps attract expert attention to findings of uncertain significance, allowing additional human input in the final interpretation, which appears especially important since the source of errors in the automated model appeared to be different than the one observed in humans. Thus it is possible that such models allowing both image detection and classification with descriptive text generation eventually augment the radiologist's work, potentially improving productivity and decreasing the error rate.[61] The availability of larger training datasets will probably allow increased performance of these automated radiology report generation models in the future.[58,59] Ultimately, such application would lighten the radiologists' work, allowing more focus on perceptual and interpretation tasks and less on report generation. Finally, automatic integration of basic measurements made on the screen (or from an ultrasonography report) into the final radiology report could be integrated during reporting.

### *Extracting Information from Radiology Reports: Report Processing*

Both structured and contextual reports, the latter allowing for adaptation of the report to the disease or clinical indication compared with a generic structured reports,[62] are increasingly used. Several advantages of structured reports have been reported, including completeness,[63] homogeneity,[64] as well as increased ability to perform data mining either for teaching files or research purposes.[64] This process is notably important and difficult in oncology follow-up, where the number of prior examinations can be significant. In machine learning studies, data labeling is often the limiting step as it requires expert annotation of large imaging datasets, which can rapidly become prohibitive. The alternative is to use the information contained within radiology reports. In this regard, structured radiological reports could potentially facilitate machine learning research in radiology by facilitating the pairing of labels to imaging data. Despite the aforementioned progressive shift toward structured reporting in radiology, there are potential drawbacks, including the lack of widespread adoption.[65] Consequently, unstructured radiology reports still represent an important source of data for many applications since this reporting format remains the one linked to most prior imaging studies currently archived in many centers. Such reports can be mined to extract weak labels for the purpose of neural network training,[66] which is especially important given the need for large datasets to achieve optimal performances with these models.[67]

Extracting unstructured information from free text has been applied with good accuracy to radiology reports using ML techniques (see **Box 1**). Historically, traditional NLP models have been used for such tasks, but this requires significant development and domain-specific feature engineering with generalizability issues.[68] Description of NLP techniques applied to radiology is beyond the scope of this article and has been reviewed in an accompanying article in this issue and elsewhere.[69,70] Deep learning approaches, including the use of neural networks (CNNs), can also be used with high accuracy for the purpose of free-text annotation without the aforementioned drawbacks associated with traditional NLP methods.[68,71] Furthermore, similar to saliency or class-activation masks used in image classification tasks, visualization tools are available to increase the interpretability of such neural networks.[68] Further improvements in model sophistication for such tasks are expected[66,68] and would allow better labeling of image data from unstructured reports, but up to a certain limit. Indeed, in 1 study, even some statements were difficult to classify by both the observers and algorithms, highlighting a potential ceiling in future improvements.[71]

During radiology study interpretation, integration of prior examinations and reports is important, a process that is time consuming but must be performed thoroughly to avoid missing important prior findings. Summarizing such information from prior reports is important, and NLP has been applied for this purpose.[72] Other applications of information extraction from radiology reports include identification of the need for follow-up imaging[73,74] and target lesion measurements in oncologic follow-ups.[75] NLP models can also be used to extract important information from other medical sources, such as pathology or clinical records, during imaging interpretation.

Radiology report translation will probably become increasingly important with globalization. A recent report shows that, although promising, the use of machine translation is not currently accurate enough to be adopted in routine clinical practice.[76] Translation of radiology reports based on a structured reporting format may be a potential approach to improve the performance of such applications.[77]

### *Quality and Safety*

At this end of this spectrum, AI can play a role in improving intradepartmental and interdepartmental as well as interdisciplinary communication for quality assurance (QA), enhanced patient safety, and educational purposes. AI tools have the potential to be used as semiautomated feedback QA tools for technologists. AI can also be used for radiologist QA in different ways, including AI-supported peer review, which can be either retrospective or prospective, the latter overlapping with computer-assisted diagnosis/diagnostic decision support functionalities of AI.[78] If sufficiently robust and well integrated into the EHR, such tools can also be used for interdisciplinary feedback and peer review based on, for example, a final pathologic diagnosis, enabling a level of continuous practice improvement and educational feedback that would not be feasible without such robust informatics systems in most health care settings. In a study, a tool allowing retrieval of pertinent follow-up information from EHRs using previously reported cases from PACS helped radiologists learn from their prior interpretations.[79] AI-supported tools can also be used to improve result communication, including critical result communication. Similar to other applications that are discussed, successful implementation of these solutions requires a well-designed informatics infrastructure. However, AI engines can further enhance these processes.

## OTHER ARTIFICIAL INTELLIGENCE APPLICATIONS FOR DIAGNOSTIC AND WORKFLOW ENHANCEMENT

### *Predictive Analytics: Diagnostic Versus Workflow Related*

Image-based prediction of treatment response or prognosis is currently the focus of important research, especially in oncology, which includes radiomic approaches based on handcrafted features or those using deep learning (**Fig. 4**).[6] Although not always characterized as such, these models can be under the broader umbrella of predictive analytics. For example, such models can predict genetic mutations,[80] pseudoprogression versus true progression,[81] and survival[82] in patients with gliomas. Another application outside of oncology is the prediction of hematoma expansion[83,84] or identification of underlying vascular malformation in acute intra-cerebral hematomas.[85] Even overall longevity can be inferred

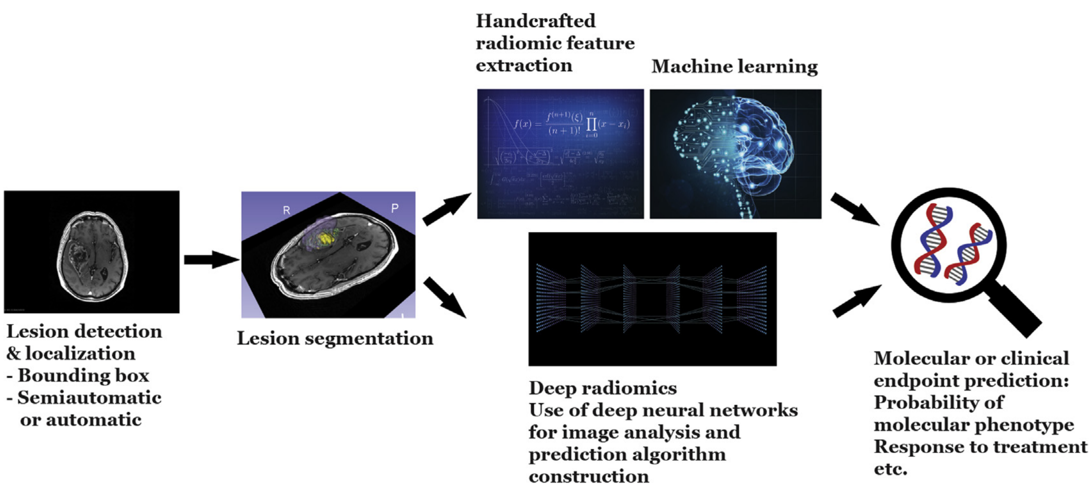


**Fig. 4.** Overview of the radiomic workflow. The major steps in the radiomic workflow consist of lesion identification and localization, segmentation, feature extraction, and prediction model construction. In the short term, lesion detection and localization may be facilitated by directing the algorithm using a bounding-box approach by the radiologist, or alternatively by the radiologist pointing at the lesion of interest using a cursor. However, in the long term, lesion identification may also be performed automatically by the algorithm. Although much of the focus in the literature has been on the diagnostic-related tasks in the radiomic workflow, any future widespread implementation and adoption in the clinical setting for routine patient care is likely to require streamlined integration into the radiologists' workflow. AI-assisted tools can also play an essential role in improving and overcoming barriers related to workflow as it pertains to advanced diagnostic medical image analysis tools and radiomics. Note that, regardless of the degree of automation, these steps would be performed under the supervision of an expert radiologist with the ability to make adjustment or modifications as needed. (*Modified from* Forghani R. Precision Digital Oncology: Emerging Role of Radiomics-based Biomarkers and Artificial Intelligence for Advanced Imaging and Characterization of Brain Tumors. *Radiology: Imaging Cancer.* 2020;2(4):e190047; with permission.)

using radiomics extracted from medical imaging.[86] A discussion of these potential AI-assisted or augmented diagnostic support tools is beyond the scope of this article. However, the application of predictive analytics is not limited to diagnostic support alone (see **Box 1**). First, even as it pertains to diagnostic predictive tasks such as that in the radiomic workflow (**Fig. 5**), any future widespread implementation and adoption in the clinical setting for routine patient care is likely to require streamlined integration into the radiologists' workflow. AI-assisted tools can play an essential role in improving and overcoming barriers related to workflow that otherwise are likely to hinder the adoption of such tools in the clinical setting.

In addition, there are other nondiagnostic predictive analytical tasks that are important for the operations in a radiology department. One example relates to applications for improving examination scheduling. In 1 study, machine learning and predictive analytics were used to identify patients who were at high risk of not attending their appointments.[87] Such applications can be important for alerting the team and implementing mitigating strategies to ensure that patients obtain the required care, along with optimizing departmental operations and efficiency. Another example is the use of predictive analytics to ensure optimal manpower needs. For example, at an academic institution, a large percentage of neuroradiologists are likely to be off service during at least part of the period of some society meetings. Using predictive analytics, this information can be used to preferentially schedule a greater percentage of nonneuroradiological, elective, nonurgent studies during that period.

## Billing and Compliance

Accurate coding of examinations and procedures is important for appropriate billing. In many jurisdictions, task is performed by identifying appropriate International Classification of Diseases (ICD) codes. Extracting such codes from electronic medical records is important for accurate payment to the hospital and doctors, and avoiding errors that may lead to unfair bills to patients, insurers, and the society. This task can be performed by ML models (see **Box 1**). Corpora of electronic medical records available to train such models, including specific radiology corpus, have been available for more than a decade.[88] Similar to other fields, neural networks have been shown to improve the accuracy of such classification tasks.[89] Further improvement has been obtained using transfer learning using classification of medical subject heading

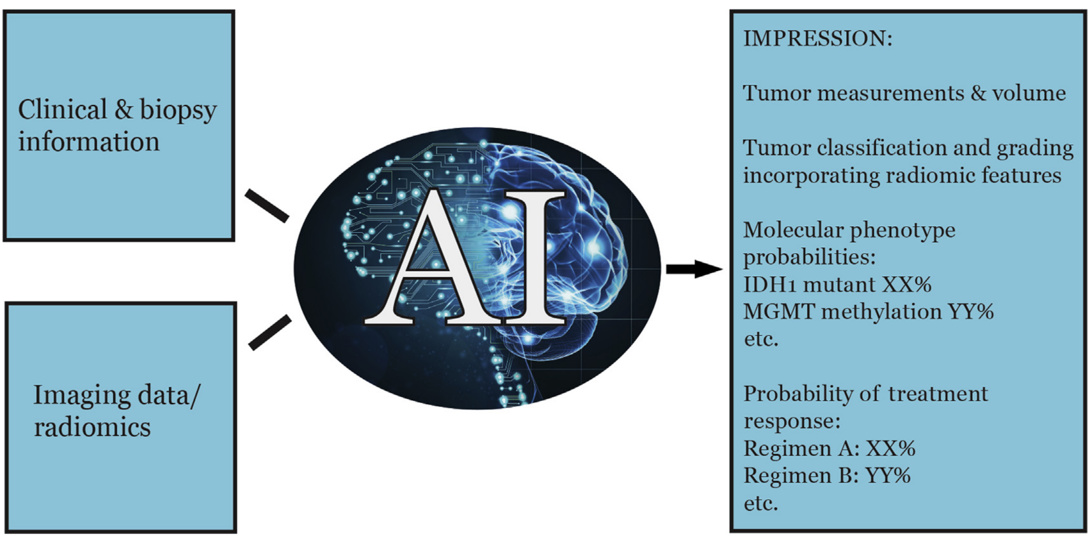


**Fig. 5.** A potential future radiology report incorporating radiomic features and machine learning for predictive modeling. A preliminary draft could even be envisaged of the report being generated automatically based on automated image analysis combined with NLP, which can then be modified by the expert radiologist as required. Seamless integration and workflow enhancement will be important requirements for successful implementation of such AI-assisted diagnostic tools. A robust, integrated informatics system powered by AI is also likely to play a role in practical aspects related to the implementation of these advanced tools, in addition to diagnostic-related functionalities. MGMT, O6-methylguanine-DNA methyltransferase. (*Modified from* Forghani R. Precision Digital Oncology: Emerging Role of Radiomics-based Biomarkers and Artificial Intelligence for Advanced Imaging and Characterization of Brain Tumors. *Radiology: Imaging Cancer.* 2020;2(4):e190047; with permission.)

(MeSH) from medical articles indexed by PubMed as the source task.[90]

A significant amount of monetary and human health care resources is lost yearly to abuse and fraud. With the advent of EHRs and computerized systems, implementation of machine learning technologies for the purpose of automated fraud detection becomes feasible.[91] Using a combination of ML and statistical methods, data mining strategies now allow the identification of a small subset of claims for further verification. Supervised and unsupervised ML techniques can be used for this purpose. One potential drawback of the former method is that supervised models need to be updated for new fraud patterns developing over time, whereas unsupervised methods may be more able to identify new types of fraud or abuse.[92] Hybrid methods combining both supervised and unsupervised methods have been used for this purpose.[91]

## SUMMARY AND FUTURE DIRECTIONS

Although diagnostic support and precision medicine applications of machine learning have garnered much attention in both the scientific community and the general public, the other important potential applications of AI in health care should not be forgotten, including those related to process improvement and operational efficiency. Various examples of such applications are discussed in this article. These applications have the potential to have significant impact on health care delivery, and by nature are likely to face fewer regulatory hurdles and easier adoption compared with more complex diagnostic image interpretation tasks. Regardless of the specific applications, machine learning–based algorithms are not currently well integrated into clinical ecosystems and often require parallel pipelines for analysis.[4,93] A robust informatics infrastructure and seamless data integration are needed to fully exploit the potential of machine learning–derived breakthroughs in health care, and they need to be prioritized to support important developments and innovations in health care that not only will improve the quality of patient care but also have the potential to improve health care system efficiency and sustainability.

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