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IMPLEMENTATION SCIENCE & OPERATIONS MANAGEMENT

Automated Notification of Relevant Expected or Incidental Findings in Imaging Exams in a Verticalized Healthcare System

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Abstract
To describe the implementation of a standardized code system for notification of relevant expected or incidental findings in imaging exams and use of an automated textual mining tool of radiological report narratives, created to facilitate directing patients to specific lines of care, reducing the waiting time for interventions, consultations, and minimizing delays to treatment. We report our 12-month initial experience with the process. A standardized code was attached to every radiology report when a relevant finding was observed. On a daily basis, the notifications was sent to a dedicated medical team to review the notified abnormality and decide a proper action. Between October 1, 2020, and September 30, 2021, 40,296 sectional examinations (CT and MR scans) were evaluated in 35,944 patients. The main findings reported were calcified plaques on the trunk of the left coronary artery or trunk like, pulmonary nodule/mass and suspected liver disease. Data of follow-up was available in 10,019 patients. The age ranged from 24 to 101 years (mean of 71.3 years) and 6,626 were female (66.1%). In 2,548 patients a complementary study or procedure was indicated, and 3,300 patients were referred to a specialist. Customized database searches looking for critical or relevant findings may facilitate patient referral to specific care lines, reduce the waiting time for interventions or consultations, and minimize delays to treatment.

Keywords Communication of findings · Practice of radiology · Radiology reports · Semi automated coding

Introduction

Healthcare often relies on evidence-based medicine. However, the unprecedented generation of clinical data brought new challenges in the visualization, analysis, and use of data in clinical decision-making, adding to this process the data-based medicine [1].

Health services currently face the arduous task of managing an increasing number of clinical and administrative data, laboratory results, and radiological reports, which are compartmentalized and leads to dissociation in global patient care. The quality improvement of health electronic records, with systematization and standardization of information, was suggested by Dixon et al. through a new structure for data management, emphasizing outcomes [2].

Imaging and laboratory tests can often identify unexpected, incidental, or critical findings that may pose a significant risk to the patient's health. Several software frameworks have been developed to facilitate data analysis, creating solutions in response to the specific demands of a health system in a customized way. Text mining and content analysis play an important role in providing evidence from patterns available in the narrative of electronic health records. Jensen et al. studied the great potential of electronic records in supporting clinical decision-making while highlighting some of the ethical, legal, and technical challenges of working on the data from these records [3].

Data processing technologies aim to provide an automated system to perform a task; in this study, we describe a computational tool to identify relevant results in imaging exams and establish rapid communication with care teams, triggering a proper action.

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The textual search of electronic medical records has already been used to evaluate the safety profile of medications and the recruitment and stratification of patients in clinical trials. The most recent publications converted the content of the unstructured text into structured records, using simple text recognition strategies. Several papers have used natural language processing to process unstructured content from electronic health records to determine disease phenotyping [1].

The rational data usage opens numerous opportunities to the health system, seeking improvements in care by extracting standardized terms, crossing clinical, laboratory, and medical imaging reports, and creating automated computational tools for mining important findings. This search may be a warning for relevant clinical abnormalities, which are essential for clinical decision-making, gaining efficiency and speed in the health care chain.

Automated identification of clinically relevant findings on imaging exams allows quick assessment of the specific abnormality and necessary action, even previous the return on physician appointment. As medical imaging reports are usually unstructured writing, data mining tasks prove to be challenging since a specific pathology can be described in several different ways.

This program was created to facilitate patient referral to specific care lines, reduce the waiting time for interventions, consultations, and minimize delays to treatment.

Objectives

Describe the implementation of a standardized code system for notification of relevant expected or incidental findings in medical exams and the benefit of an automated textual mining tool of radiological report narratives seeking these findings to target patients to a specific line of care.

Method

To guarantee automated search through reliable and effective textual mining, a code list was created for the most relevant clinical findings observed in the imaging exams, based on the historical frequency and relevance of significant findings in our health service. According to the institutional protocol, these codes are routinely inserted in the reports by radiologists, so every exam must receive at least one code.

The codifying list includes three large groups:

- Exam with relevant findings categorized by specific code
- Exam without abnormal findings or with findings of no clinical relevance
- Exam with relevant findings not classified by institutional codification

In Table 1, we present the code list for MRI or CT exams.

Whenever one of the coded findings is described, the radiologist adds the corresponding code at the end of the report.

Generating actionable intelligence for doctors to act upon involves several databases and properly designed computed scripts. Daily, a computed script, created in Python language, consults and extracts from the RIS (Radiology Information System) database the reports of exams performed on the previous day and stores them on our service's SQL database. Then, another computed script, also created in Python language, performs textual mining to extract the codes from the reports and updates a selected base of medical reports and codes. The information is then pulled to a Microsoft PowerBI cloud, which updates several dashboards used by a dedicated geriatrics team.

From dashboard data and after reviewing the patient's electronic medical record, the geriatrician team member defines the conduct related to the reported finding. First they check if the reported finding is already known to the patient's referral physician and already had appropriate specific management, if so the case is concluded with no further action. Therefore, if the reported finding was unknown or has not yet been adequately managed, the geriatrician directs the case according to the institutional protocol. A standardized action was defined for each code, including evaluation with specialists, performing complementary diagnostic investigation, or directing the patient to a specific treatment.

After approval by the Institutional Research Ethics Committee, under CAAE 43,084,721.0.0000.8114, on February 24, 2021, data were collected and analyzed to audit the preliminary results of this program. This single-center, descriptive, and analytical retrospective study analyzed the notifications from CT, and MRI reports performed in a verticalized healthcare system from October 2020 to September 2021, including outpatients and inpatients.

According to institutional protocol, critical diagnoses such as pulmonary embolism or pneumoperitoneum, are part of another program, with a dedicated list of codes and requiring immediate notification to the referring physician, so they were not analyzed in this study.

From data flows configured in the various institutional databases and electronic health records (EHR), mining and data extraction techniques were performed in CT and MR reports, creating a database with incremental and automatic updating. Using extraction and transformation tools (SQL database queries and Python scripts) and Power BI data analysis®, we continuously monitored the data of this patient group over time (codification system dashboard). The data is stored primarily in Microsoft SQL Server, and all processing is performed using Jupyter Notebook running the Python 3.5 + kernel.

The exploratory analysis was performed employing summary measures (mean, standard deviation, median, minimum, maximum, frequency, and percentage).

Table 1 Code list for MRI or CT exams

Departament	Radiologic Findings	Code (MRI/CT)
1. Head and Neck Surgery	Non-thyroid cervical suspected lesion	#FC1_D1
	Facial tumor	#FC1_D2
2. Surgical Oncology	Suspected hepatic lesion	#FC2_D1
	Pancreatic suspected lesion: solid or cystic	#FC2_D2
	Adnexal lesions (septate, solid component, diameter > 5 cm)	#FC2_D3
	Retroperitoneal mass	#FC2_D4
	Tumor/lesion/polyp in gallbladder > 1 cm	#FC2_D5
	Ascites associated with gynecological findings: usually associated with ovarian or	#FC2_D6
	peritoneal nodules	#FC2_D7
	Suspected uterine lesions, non-myomatous	#FC2_D8
	Soft tissue tumor	#FC2_D9
	Ovarian lesion O-RADS 3	
3. Thoracic Surgery	Pulmonary lesion/mass	#FC3_D1
	Pleural/mediastinal mass	#FC3_D2
4. Vascular Surgery	Abdominal aortic aneurism, diameter > 4,5 cm	#FC4_D2
5. Hematology	Suspected lymphadenopathy	#FC5_D1
	Multiple myeloma	#FC5_D2
6. Hepatology	Cirrhosis	#FC6_D1
	Suspected liver disease	#FC6_D2
7. Neurology	CNS tumor	#FC7_D1
	Cerebral aneurism > 0,7 cm	#FC7_D2
	Arteriovenous malformation	#FC7_D3
9. Endoscopic Methods	Esophagus, stomach, or duodenum wall thickness/nodule/mass	#FC9_D1
	Colonic wall thickness/nodule/mass	#FC9_D2
10. Clinical Oncology	Lung metastasis	#FC10_D1
	Liver metastasis	#FC10_D2
	Bone metastasis	#FC10_D3
11. Orthopaedy	Bone tumors	#FC11_D1
	Single bone lesion	#FC11_D2
12. Pneumology	Pulmonary fibrosis	#FC12_D1
	Severe pulmonary emphysema	#FC12_D2
13. Urology	Obstructive kidney calculi	#FC13_D1
	Complex renal cyst (Bosniak III or IV)	#FC13_D2
	Adrenal mass > 4 cm	#FC13_D3
	Bladder mass < 3 cm	#FC13_D4
	Bladder mass ≥ 3 cm	#FC13_D5
	Renal nodule/mass	#FC13_D6
14. Cardiology	Calcified plaques on the trunk of the left coronary artery or trunk like	#FC14_D1
15. Geriatrics	Osteoporotic vertebral fractures	#FC15_D1
16. Operational Flow	Normal exam	#FC16_D1
	Findings of no clinical relevance	#FC16_D2
	Clinically relevant findings not classified by specific code	#FC16_D3

Results

Between October 1, 2020, and September 30, 2021, 40,296 sectional examinations (CT and MR scans) were evaluated in 35,944 patients. Table 2 shows the most frequently reported codes. In addition to the findings reported by specific code, we observed 10,344 patients codified for relevant findings not classified by institutional codification and 10,946 were codified for findings without clinical relevance.

From the total of 35,944 patients, we observed that 24,998 (69.5%) patients had at least one relevant clinical finding. From this group of relevant clinical findings, 10,019 patients had complete follow-up data available, with 3,393 male patients (33.9%) and 6,626 females (66.1%). The age of patients ranged from 24 to 101 years (mean of 71.3 years, median of 72 years). The majority of patients were not followed up by any specialist (7,573 / 75.6%), while 2,403 (24.0%) were already followed by some specialty, and 2,536 (25.3%) patients needed a complementary study or procedure. After evaluation of the electronic medical record or additional complementary tests, 3,323 (33.2%) patients were referred to specialists, most of which for thoracic surgery (Table 3).

Table 2 Number and percentage of the most notified codes in relation to the total of CT and MRI exams (n = 40,296)

Diagnosis/code	Number	%
Findings of no clinical relevance	10,946	27.2
Clinically relevant findings not classified by specific code	10,344	25.7
Calcified plaques on the trunk of the left coronary artery or trunk like	7,603	18.9
Pulmonary nodule/mass	1,793	4.4
Suspected liver disease—nonspecific textural or morphological alteration	879	2.2
Osteoporotic vertebral fractures	733	1.8
Thickening/nodule/colon mass	659	1.6
Renal nodule/mass	511	1.3
Viral pneumonia (COVID)	434	1.1
CNS tumors	415	1.0
Suspected pancreatic lesion: complex nodule or cyst	387	0.9
Liver cirrhosis	330	0.8
Thickening/nodules/mass in the esophagus, stomach, and duodenum	285	0.7
Suspected liver nodule for malignancy	242	0.6

Included in the table all codes found more than 200 times

In 6,481 (64.7%) patients, the recommended action for incidental finding has been completed, and the patient was captured, performed tests, and directed to the specialist. In 137 cases, contact with patients did not occur, and it was considered unsuccessful after three attempts to contact. One hundred seventy-one patients missed consultation or complimentary examination. Some outcomes were found at the time of contact of the gerontology team, including 294 patients hospitalized at the time of the contact and 383 who had died. Further, 125 patients preferred to postpone care due to the COVID19 pandemic, 91 patients refused care and 305 patients, after case review, did not require additional action.

Discussion

Artificial Intelligence (AI) has permeated all fields and aspects of medical practice and improved healthcare in recent years. AI techniques can be an exciting tool to analyze radiology reports and extract clinically relevant findings [4].

Active extraction of relevant findings can impact patient care, reducing the time between steps and the number of steps in the care line. Imaging reports detail the radiological findings that could answer a specific clinical question. However, it is not uncommon to identify unexpected radiological findings unrelated to clinical suspicion. For example, detecting incidental pulmonary mass in a preoperative chest X-ray may be a relevant finding that should be prioritized. Early communication is essential for safe and effective healthcare.

Currently, there is a tendency to communicate critical results to physicians or directly to patients, but not noncritical relevant findings. Radiologists have the most significant problem when communicating unexpected critical findings, especially in outpatient exams [5]. Communication in radiology is one of the most relevant activities, but it is time-consuming and sometimes not auditable. It is convenient to have automated systems to assume these actions. Machine Learning (ML) can play an essential role in these situations [6], providing systems capable of learning and improving automatically from experience.

In this series, with predominantly elderly patients, we observed that most CT or MRI scans showed some clinically relevant findings (24,998 patients / 69.5%). From the 10,019 patients with complete follow-up data available, the majority of patients were not followed up by any specialist (75.6%), and 2,536 (25.3%) patients needed a complementary study or procedure. After reviewing the case or performing additional workup, 3,323 (33.2%) patients were referred to specialists. Among the most frequently reported codes at Table 2, a significant percentage corresponds to suspicious findings for malignancy, totaling 4,292 (10.7%) notifications in the total of 40,296 CT or MRI exams. The most frequent suspicious finding for malignancy was pulmonary nodule/mass, and, consequently, the specialty that received the highest number of referrals was thoracic surgery.

Similar to our results, Olthof et al. in 2020, studying the implementation of structured reports to improve communication of critical findings, showed that "oncology" was one of the most often occurring categories, where the time to establish conduct can significantly impact the outcome [7]. Detecting and treating cancer at an early stage can and does

Table 3 Additional examinations or additional procedures, and complementary post-exam referrals

	Events	N (%)	Total
Additional Exams and Procedures	Computed Tomography (CT)	774 (30.5)	2,536
	Magnetic Resonance (MR)	617 (24.3)	
	Percutaneous biopsy	180 (7.1)	
	Established hepatopathy protocol (Ultrasound with Elastography)	179 (7.1)	
	Schedule consultation with another specialty	150 (5.9)	
	Colonoscopy	148 (5.8)	
	Mammogram	127 (5.0)	
	Preoperative evaluation	68 (2.7)	
	Upper digestive endoscopy (AED)	58 (2.3)	
	Established cirrhosis protocol (Doppler and HCC screening + Endoscopy)	54 (2.1)	
	Ultrasound	52 (2.0)	
	Hysteroscopy	42 (1.7)	
	Possible invasive investigation/scheduling appointment	40 (1.6)	
	Scintigraphy	16 (0.6)	
	Colonoscopy + Endoscopy	13 (0.5)	
	Upper digestive echoendoscopy	10 (0.4)	
	Doppler	8 (0.3)	
Post-exam referrals	Thoracic surgery	947 (28.5)	3,323
	Urology	656 (19.7)	
	Vascular surgery	279 (8.4)	
	Hepatology	210 (6.3)	
	Pulmonology	199 (6.0)	
	Clinical Oncology	180 (5.4)	
	Surgical Oncology	129 (3.9)	
	Clinical Gastroenterology	129 (3.9)	
	Review of referral criteria	114 (3.4)	
	Head and Neck Surgery	88 (2.6)	
	Gynaecology	84 (2.5)	
	Neurosurgery	70 (2.1)	
	Digestive surgical oncology	54 (1.6)	
	Haematology	31 (0.9)	
	Geriatrics	27 (0.8)	
	Orthopedics	26 (0.8)	
	Clinical Neurology	23 (0.7)	
	Mastology	18 (0.5)	
	Endocrinology	16 (0.5)	
	Palliative care	14 (0.4)	
	General Surgery	11 (0.3)	
	Coloproctology	11 (0.3)	
	Internal Medicine	7 (0.2)	

save lives. Survival rates improve dramatically when cancer is diagnosed early and is more likely to be treated successfully. Another important aspect relating to early diagnosis is treatment costs given that it is much less costly to treat cancer in early stages [8, 9].

To implement a program like this, besides training radiologists on the proper and routine use of codes in their reports, it is necessary to have a team and system availability to use automation tools. However, we believe that the cost of such an implementation can be offset by ensuring earlier diagnoses and more assertive medical referrals, in addition to a better patient experience. Clinically inappropriate referrals can lead to poorer health outcomes for patients, ineffective use of doctors' time, and unnecessary costs to the patient and the health system.

From this survey of our initial experience, we observed some limitations and improvement points, like reevaluating the less frequently used codes and developing pathology-centered activities for the most frequent abnormalities. Further, we intend to review the group of exams "with relevant findings not classified by institutional codification," second in frequency in our casuistic, to verify the most common pathologies and add specific codes. We also highlight the partial analysis of our casuistic as a limitation of our study: from 24,998 patients with at least one relevant finding reported, only 10,019 were concluded and had all follow-up data available at the time of this survey.

In conclusion, the results of this study showed that it is possible to create a system to facilitate and ensure adequate notification and management of relevant clinical findings observed in imaging exams. To improve patient care or experience, facilitate the workflow and avoid adverse clinical outcomes, we can customize database automated searches, looking for critical or relevant findings, which may trigger a chain of actions capable of minimizing the time to take meaningful action.

Authors' contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by ENOF, FPM and MFAA. The first draft of the manuscript was written by FPM, MFAA and PNVPB. All authors read and approved the final manuscript.

Declarations

Ethical approval This research received approval from the institution's Research Ethics Committee (CAAE 43084721.0.0000.8114, approved on February 24, 2021).

Informed consent The written informed consent was not required by the institution's Research Ethics Committee.

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

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