Labelling imaging datasets on the basis of neuroradiology reports: a validation study

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Abstract. Natural language processing (NLP) shows promise as a means to automate the labelling of hospital-scale neuroradiology magnetic resonance imaging (MRI) datasets for computer vision applications. To date, however, there has been no thorough investigation into the validity of this approach, including determining the accuracy of report labels compared to image labels as well as examining the performance of non-specialist labellers. In this work, we draw on the experience of a team of neuroradiologists who labelled over 5000 MRI neuroradiology reports as part of a project to build a dedicated deep learning-based neuroradiology report classifier. We show that, in our experience, assigning binary labels (i.e. normal vs abnormal) to images from reports alone is highly accurate. In contrast to the binary labels, however, the accuracy of more granular labelling is dependent on the category, and we highlight reasons for this discrepancy. We also show that downstream model performance is reduced when labelling of training reports is performed by a non-specialist. To allow other researchers to accelerate their research, we make our refined abnormality definitions and labelling rules available, as well as our easy-to-use radiology report labelling app which helps streamline this process.

Keywords: Natural language processing · Deep learning · Labelling.

1 Introduction

Deep learning-based computer vision systems hold promise for a variety of applications in neuroradiology. However, a rate-limiting step to clinical adoption is the labelling of large datasets for model training, a laborious task requiring
considerable domain knowledge and experience. Following recent breakthroughs in natural language processing (NLP), it is becoming feasible to automate this task by training text classification models to derive labels from radiology reports and to assign these labels to the corresponding images [12][13][14][7]. To date, however, there has been no investigation into the general validity of this approach, including determining the accuracy of report labels compared to image labels as well as assessing the performance of non-specialist labelers.

In this work we draw on the experience of a team of neuroradiologists who labelled over 5000 magnetic resonance imaging (MRI) neuroradiology reports as part of a project to build a dedicated deep learning-based neuroradiology report classifier. In particular, we examine several aspects of this process which have hitherto been neglected, namely (i) the degree to which radiology reports faithfully reflect image findings (ii) whether the labelling of reports for model training can be reliably outsourced to clinicians who are not specialists (here we examined whether the performance of a neurologist or radiology trainee (UK registrar grade; US resident equivalent) is similar to that of a neuroradiologist) (iii) the difficulty of creating an exhaustive and consistent set of labelling rules, and (iv) the extent to which abnormalities labelled on the basis of examination-level reports are detectable on MRI sequences likely to be available to a computer vision model.

Overall, our findings support the validity of deriving image labels from neuroradiology reports, but with several important caveats. We find that, contrary to basic assumptions often made for this methodology, radiological reports are often less accurate than image findings. Indeed, certain categories of neuroradiological abnormality are inaccurately reported. We conclude that, in our experience assigning binary labels (i.e. normal vs abnormal) to images from reports alone is very accurate. The accuracy of more granular labelling, however, is dependent on the category, and we highlight reasons for this discrepancy.

We also find that several aspects of model training are more challenging than is suggested by a review of the literature. For example, designing a complete set of clinically relevant abnormalities for report labelling, and the rules by which these were applied, took our team of four neuroradiologists more than six months to complete with multiple iterations, and involved the preliminary inspection of over 1,000 radiology reports. To allow other researchers to bypass this step and accelerate their research, we make our refined abnormality definitions and labelling rules available. We also make our radiology report labelling app available which helps streamline this manual annotation process. Importantly, we found that even when enabled with the labelling app and set of abnormalities and rules, report annotation for model training must be performed by experienced neuroradiologists, because a considerable reduction in model performance was seen when labelling was performed by a neurologist or a radiology trainee.
2 Related work

NLP models have previously been employed to assign image labels in the context of training computer vision models for neuroradiology applications using radiology reports from both computed tomography (CT) [12][14][9] and MRI [13] examinations. In all cases, classification performance was reported for the primary objective of labelling reports. However, there was no comparison of either the predicted or annotated labels with the images. The closest published work to our paper is therefore a conference abstract highlighting discrepancies between the findings detailed in chest radiograph reports and the corresponding images when labelling a limited set of abnormalities [8]. To the best of our knowledge no such investigation has been performed in the context of neuroradiology, nor have the challenges of creating an NLP labelling tool for neuroradiology applications been described.

Previous work has investigated the accuracy of using crowdsourcing to label images in the context of general [5] as well as medical [4] computer vision tasks. However, we know of no work in the context of neuroradiology which investigates the level of expertise required for accurate manual annotation of reports. Although it might seem obvious that experienced neuroradiologists are required for this task, previous works have instead employed post-graduate radiology and neurosurgery residents [14] or attending physicians [12][9], without providing any insight into the possible reduction in labelling accuracy that such delegation may invite.

Automated brain abnormality detection using either T2-weighted or diffusion-weighted images (DWI) and employing supervised [11][10] and unsupervised [2] deep learning models has previously been reported. However, in each case only a limited set of abnormalities were available during training and testing, and there was no investigation into the range of abnormalities likely to be detected by the computer vision system using only these sequences. In fact, to the best of our knowledge no investigation has determined what fraction of abnormalities are visible to expert neuroradiologists inspecting only a limited number of sequences. Resolving this point could help narrow the architecture search space for future deep learning-based abnormality detection systems.

3 Data and methods

The UKs National Health Research Authority and Research Ethics Committee approved this study. 126,556 radiology reports produced by expert neuroradiologists (UK consultant grade; US attending equivalent), consisting of all adult (> 18 years old) MRI head examinations performed at Kings College Hospital NHS Foundation Trust, London, UK (KCH) between 2008 and 2019, were included in this study. The reports were extracted from the Computerised Radiology Information System (CRIS) (Healthcare Software Systems, Mansfield, UK) and all
data was de-identified. Over the course of more than twelve months, 5000 reports were annotated by a team of neuroradiologists to generate reference standard report labels to train the neuroradiology report classifier described in [13] (ALARM classifier). Briefly, each unstructured report was typically composed of 5-10 sentences of image interpretation, and sometimes included information from the scan protocol, comments regarding the patient’s clinical history, and recommended actions for the referring doctor. In the current paper, we refer to these reference standard labels generated on the basis of manual inspection of radiology reports as silver reference standard labels. Prior to manual labelling, a complete set of clinically relevant categories of neuroradiological abnormality, as well as the rules by which reports were labelled, were generated following six months of iterative experiments involving the inspection of over 1000 radiology reports. The complete set of abnormalities, grouped by category, are presented in Appendix A.

Three thousand reports were independently labelled by two neuroradiologists for the presence or absence of any of these abnormalities. We refer to this as the ‘coarse dataset’ (i.e. normal vs. abnormal). Agreement between these two labellers was 94.9%, with a consensus classification decision made with a third neuroradiologist where there was disagreement. Separately, 2000 reports were labelled by a team of three neuroradiologists for the presence or absence of each of 12 more specialised categories of neuroradiological abnormality (mass e.g. tumour; acute stroke; white matter inflammation; vascular abnormality e.g. aneurysm; damage e.g. previous brain injury; Fazekas small vessel disease score [6]; supratentorial atrophy; infratentorial atrophy; foreign body; haemorrhage; hydrocephalus; extra-cranial abnormality), described in detail in Appendix A. We refer to this as the granular dataset. There was unanimous agreement between these three labellers across each category for 95.3% of reports, with a consensus classification decision made with all three neuroradiologists where there was disagreement.

We manually inspected 500 images (comprising, on average, 6 MRI sequences) to generate reference standard image labels. We refer to labels generated in this way as gold reference standard labels. 250 images were labelled for the presence or absence of any abnormality, systematically following the same criteria as that used to generate the coarse report dataset. Similarly, 250 images were examined and given 12 binary labels corresponding to the presence or absence of each of the more granular abnormality categories.

Our team designed a complete set of clinically relevant categories capable of accurately capturing the full range of pathologies which present on brain MRI scans. The aim here was to try and emulate the behaviour of a radiologist in the real world, guided by the need for clinical intervention for an abnormal finding. To help other researchers bypass this step, and to encourage standardization across research groups of abnormality definitions, we make our abnormality categories, as well as all clinical rules, available in Appendix
A. Our manual labelling campaign was considerably aided by our development of a dedicated labelling app. This app allows easy visualisation and labelling of reports through a graphical user interface (GUI), and includes functionality for flagging difficult cases for group consensus/review. Two apps were developed - one for binary labelling (Figure 1), and one for more granular labelling (Figure 2) - and we make both available to other researchers at https://github.com/MIDIconsortium/RadReports.

**Fig. 1.** Binary report labelling tool for the MR Imaging abnormality Deep learning Identification (MIDI) study. The example report should be marked as normal.

**Fig. 2.** Granular report labelling tool for the MIDI study. The correct labels for this example report have been selected.
4 Results

4.1 Impact of annotator expertise

To assess the level of expertise required to perform manual annotation of reports for training a text classification model, two experiments were performed.

First, we compared the coarse labels (i.e. normal vs. abnormal) generated by a hospital doctor with ten years experience as a stroke physician and neurologist, who was trained by our team of neuroradiologists over a six month period, with neuroradiologist-generated labels. The rationale for determining the performance was twofold. Neurologists and stroke physicians frequently interpret reports held on the Electronic Patient Record during patient consultations, therefore it is expected that they would be able to differentiate, and therefore label, normal or abnormal reports accurately. Moreover, given that there are less neuroradiologists than neurologists or stroke physicians, with a ratio of 1:4 in the UK, it is likely to be easier to recruit such physicians to perform such labelling tasks.

We found a reduction in performance of neurologist labelling when compared to the labels created by an expert neuroradiologist (Table 1). Based on classification and evaluation methodology in [13], the state-of-the-art ALARM classifier was trained using these neurologist-derived labels and, for comparison, labels generated by a blinded neuroradiologist (Figure 3). The corresponding reduction in classification performance on a hold-out test set of silver reference-standard labels (i.e. reports with consensus) at an arbitrarily fixed sensitivity of 90% (Table 2) demonstrates the impact of what we have shown to be a sub-optimal labelling strategy. In summary, there is optimal performance when the classifier is trained with reports labelled by an experienced neuroradiologist.

| Table 1. Labelling performance of a stroke physician and neurologist. |
|-------------------------------------------------|
| Accuracy (%) | Sensitivity (%) | Specificity (%) |
| 92.7          | 77.2            | 98.9            |

| Table 2. Accuracy, specificity, and F1 score of a neuroradiology report classifier trained using data labelled by either a neurologist or neuroradiologist operating at a fixed sensitivity of 90%. Best performance in bold. |
|-------------------------------------------------|
| Annotator       | Accuracy (%) | Specificity (%) | F1 (%) |
| Neurologist     | 89.8         | 89.5            | 75.8   |
| Neuroradiologist| **96.4**     | **97.7**        | **90.3**|

As a second experiment, a 3rd year radiology trainee who was also trained by our team over a six month period to label neuroradiology reports, gener-
Fig. 3. ROC curve for a neuroradiology report classifier trained on labels generated by a neurologist (cyan) and a neuroradiologist (blue). The area under the curve (AUC) is shown.

...ated labels for our ‘granular dataset. There was a reduction in radiology trainee performance, averaged across all 12 binary labels, when compared to the silver reference standard labels created by our team of expert neuroradiologists (Table 3). The sensitivity of these labels is clearly too low to be used for model training.

Table 3. Labelling performance of a radiology trainee on the ‘granular dataset’, averaged across all 12 binary labels.

| Sensitivity (%) | Specificity (%) | F1 (%) |
|----------------|----------------|--------|
| 64.4           | 98.3           | 70.8   |

It is worth highlighting that reliability (inter-rater agreement) and accuracy (performance) should not be conflated for labelling tasks. We demonstrate this in a further experiment where the same neurologist previously described also generated labels for our ‘granular dataset’. The Fleiss \( \kappa \) score for the radiology trainee and the neurologist averaged over all 12 binary categories was 0.64, which is above the threshold previously employed to establish neuroradiology label reliability[14]. Substantial inter-rater agreement (commonly taken as \( \kappa > 0.6 \)), therefore, does not necessarily equate to label accuracy as this experiment has shown.

4.2 Report validation

To determine the validity of assigning image labels on the basis of radiology reports, the granular labels derived from reports (silver reference standard) were
compared to those derived by inspecting the corresponding images (gold reference standard) for 500 cases (Table 4). Although the false positive rate of report labelling is very low for the 12 granular categories of interest, it is clear that the sensitivity of radiology report labelling is category dependent and can be low. On further analysis, we found that insensitive labelling for any given category typically reflects the absence of any reference in the report to that particular category rather than a discrepancy in interpretation. The categories with low sensitivity include hydrocephalus, haemorrhage, extra-cranial abnormalities, and infratentorial atrophy. The reasons for this are discussed below.

### Table 4. Accuracy of silver reference standard report labels for granular categories when compared to the corresponding gold standard image labels. Categories with sensitivity > 80% in bold.

| Category                | Sensitivity (%) | Specificity (%) | F1 (%) |
|-------------------------|----------------|-----------------|--------|
| Fazekas                 | 90.5           | 95.6            | 93.2   |
| Mass                    | 97.9           | 93.6            | 95.9   |
| Vascular                | 83.3           | 88.4            | 86.5   |
| Damage                  | 82.4           | 92.7            | 87.8   |
| Acute Stroke            | 94.4           | 99.5            | 94.4   |
| Haemorrhage             | 69.2           | 99.6            | 78.3   |
| Hydrocephalus           | 70.0           | 99.6            | 77.8   |
| White Matter Inflammation| 95.6          | 100             | 97.7   |
| Foreign Body            | 100.0          | 99.6            | 96.6   |
| Extracranial abnormality| 60.0           | 94.7            | 54.5   |
| Supratentorial Atrophy  | 100            | 94.6            | 76.9   |
| Infratentorial Atrophy  | 77.7           | 94.3            | 54.5   |
| Average                 | 85.1           | 96.0            | 82.8   |

Importantly, silver standard binary labels indicating the presence or absence of any abnormality in a report (i.e. normal vs. abnormal) were accurate when compared to the image (gold reference standard label) (Table 5).

### Table 5. Accuracy of silver reference standard report labels for binary categories (i.e. normal vs abnormal) relative to the corresponding gold standard image labels.

| Category                   | Sensitivity (%) | Specificity (%) | F1 (%) |
|----------------------------|-----------------|-----------------|--------|
| Normal vs. abnormal        | 98.7            | 96.6            | 98.5   |

### 4.3 MRI sequences and abnormality visibility

In another experiment we examined the utility of assigning examination-level labels derived from radiology reports to different MRI sequences. In general,
neuroradiology reports detail findings from multi-modality (i.e. multiple MRI sequences) imaging examinations, with individual sequences providing complementary information to discriminate specific tissues, anatomies and pathologies. For example, the signal characteristics of blood changes over time, the rate of which is sequence dependent. Therefore analysis of images from multiple sequences allows the chronicity of a haemorrhage to be deduced. Assigning the same label to all images in a multi-modality examination can confound computer vision classification if a model isn’t optimised to take as its input the individual sequence from which a particular examination-level label was derived. Therefore, we wished to determine whether a minimal number of sequences would be sufficient for use with report-derived labels. At our institution, axial T2-weighted and DWI images are typically obtained for routine image review, with over 78% of patients receiving both images during an examination. We sought to determine what fraction of abnormalities are visible to a neuroradiologist inspecting only the T2-weighted and DWI images. Binary labels (i.e. normal vs. abnormal) for 250 examinations were generated by inspecting only these sequences, and compared to labels derived from all available sequences for the same examinations. The agreement between these two labels was over 97%, showing that these two sequences would be sufficient for use with report-derived labels for most abnormality detection tasks. Examples of the wide range of abnormalities identified on the basis of T2-weighted and DWI imaging appear in Table 6.

Table 6. Examples of abnormalities detected from axial T2 and DWI sequences only

| Acute infarction, neurosarcoidosis, polymicrogyria, hypoxic ischemic brain injury, arachnoid cyst, cerebellar haemangioma, Behcet’s vasculitis, thalamic haematoma, high grade glioma, occipital lymphoma, sebaceous cyst, periventricular heterotopia, pontine angle epidermoid cyst, white matter injury, mature infarct, parafalcine meningioma, mucosal retention cyst, cavernoma, neurodegeneration, cerebellar tonsillar ectopia, demyelination, white matter inflammation, aneurysm, small vessel ischaemic change, convexity meningioma, Alzheimer’s disease, parietal lobe haemorrhage |

5 Discussion

In this work we have examined several assumptions which are fundamental to the process of deriving image labels from radiology reports. Overall, our findings support the validity of deriving image labels from neuroradiology reports. In particular, assigning binary labels (i.e. normal vs abnormal) to images from reports alone is highly accurate and therefore acceptable. Until now this has been assumed but has not been thoroughly investigated. The accuracy of more granular labelling, however, is dependent on the category. For example, labelling of acute stroke, mass, neuro-degeneration, and vascular disorders, is shown to
be accurate.

The low labelling accuracy seen in some granular labelling categories is a result of low sensitivity. Low sensitivity typically reflects the absence of any reference in the report to that particular category rather than a discrepancy in interpretation. A qualitative analysis by our team of neuroradiologists has determined several reasons for low sensitivity in some categories.

First, in the presence of more clinically important findings, neuroradiologists often omit descriptions of less critical abnormalities which may not necessarily change the overall conclusion or instigate a change in the patients management. For example, on follow-up imaging of previously resected tumours, we have found that the pertinent finding as to whether there is any progressive or recurrent tumour is invariably commented on. In contrast, the presence of white matter changes secondary to previous radiotherapy appears less important within this clinical context. If unchanged from the previous imaging, a statement to the effect of otherwise stable intracranial appearances is typical in these cases.

A second source of low sensitivity is the observation that radiology reports are often tailored to specific clinical contexts and the referrer. A report aimed at a neurologist referrer who is specifically enquiring about a neurodegenerative process in a patient with new onset dementia, for example, may make comments about subtle parenchymal atrophy. In contrast, parenchymal volumes may not be scrutinised as closely in the context of someone who has presented with a vascular abnormality, such as an aneurysm, and a report is aimed at a vascular neurosurgeon. Both sources of low sensitivity mentioned above often reflect a satisfaction of search error where the radiologist has failed to appreciate the full gamut of abnormalities. After identifying one or two abnormalities the task may appear complete and there is less desire to continue to interrogate the image [1]. It is also noteworthy that abnormalities which are identified by the neuroradiologist by chance may be judiciously omitted from the report on a case by case basis when such incidentalomas are thought to be of little consequence. Because of these sources of low sensitivity, labelling categories of abnormality from radiology reports remains challenging for haemorrhage (note that acute haemorrhage is typically detected by CT; MRI reports were often insensitive to those haemorrhages associated with non-critical findings such as micro-haemorrhages), hydrocephalus, extracranial abnormalities and infratentorial atrophy.

In addition to examining the accuracy of radiology reports compared to image findings, we have also demonstrated that most abnormalities typical of a real-world triage environment are picked up using only T2-weighted and DWI sequences. This observation may help narrow the architecture search-space for future deep learning-based brain abnormality detection systems, and allow a more accurate comparison of model performance across research groups. However, there are certain abnormalities which may not be visible on these sequences.
For example, the presence of microhaemorrhages or blood breakdown products (hemosiderin), are sometimes only visible on gradient echo ($T_2^*$-weighted) or susceptibility weighted imaging (SWI) [3]. Furthermore, foci of pathological enhancement on post contrast $T_1$-weighted imaging can indicate underlying disease which may not be apparent on other sequences. Therefore, whilst we have shown that using $T_2$-weighted and DWI sequences alone allows almost all abnormalities to be identified visually, and that plausibly this will translate to efficient computer vision training tasks, it is important to be aware that there are potential limitations.

We briefly discuss several logistical aspects of the report labelling process which were not covered by our more quantitative investigations. Our team designed a complete set of clinically relevant categories capable of accurately capturing the full range of pathologies which present on brain MRI scans. The aim here was to try and emulate the behaviour of a radiologist in the real world, guided by the need for clinical intervention for an abnormal finding. This process, however, was more onerous than is often presented in the literature, requiring the inspection of over 1000 radiology reports by our team of experienced neuroradiologists over the course of more than six months before an exhaustive and consistent set of abnormality categories, as well as the rules by which reports were to be labelled, could be finalised. The rules and definitions constantly evolved during the course of the practice labelling experiments. To allow other researchers to bypass this step and accelerate their research, we make our refined abnormality definitions and labelling rules available as well as our dedicated labelling easy-to-use app.

6 Conclusion

We conclude that in our experience, assigning binary labels (i.e. normal vs abnormal) to images from reports alone is highly accurate. Importantly, we found that even when enabled with the labelling app and set of abnormalities and rules, annotation of reports for model training must be performed by experienced neuroradiologists, because a considerable reduction in model performance was seen when labelling was performed by a neurologist or a radiology trainee. In contrast to the binary labels, the accuracy of more granular labelling is dependent on the category.

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A  MR Imaging abnormality Deep learning Identification study (MIDI) neuroradiology abnormality classification definitions

Preliminary notes:

1. Please use both the CLINICAL INFORMATION (immediately above the report) and the REPORT when labelling as both can provide clues as to how to label
2. The SKIP button is to be used if entirely unsure
3. The CONSENSUS button is to be used if nuanced and needs decision by group
4. Anything slightly ambiguous to the labeller should be skipped or go to consensus required - never guess
5. When there is a differential diagnosis, if it is clear the lesion is very much non-specific and is described as A or B it is OK to label both A and B. However, if the report is clearly leading the reader towards A and only mentioning the other differential i.e. B as a mere possibility then we label as A. An example might be of the report saying something like enhancement in the resection cavity likely represents normal post-operative appearances, however residual tumour cannot be entirely excluded this should be labelled as damage and not tumour (see category rules below)
6. Midline shift would typically be seen in the context of another abnormality. The primary pathology should be labelled only e.g. tumour or acute/subacute stroke
7. Similarly, vasogenic oedema would typically be seen in the context of another abnormality. The primary pathology should be labelled only e.g. tumour
8. Post surgical pituitary scans will be put into CONSENSUS box due to the difficulty of determining from report whether there is a cavity (damage) or not unless this is clearly described within the report
9. Craniotomies & craniectomies & burr holes
   - Consensus is that as we want a classifier to ignore these so we would NOT label as extra-cranial abnormality and instead we ignore it
   - However, if lots of metalwork was involved e.g. in a cranioplasty (or the occasional craniotomy which still contains some metalwork) artefact, given the extreme MRI signal distortion we felt that this should be labelled as foreign body
10. Cervical spine and other non-head MRIs contained in addition to MRI heads should be ignored
11. if artefact then use Bad Scan button

A.1  Fazekas

[6] gives a classification system for white matter lesions (WMLs):

1. Mild - punctate WMLs: Fazekas I
2. Moderate - confluent WMLs: Fazekas II
3. Severe - extensive confluent WMLs: Fazekas III

To create a binary categorical variable from this system, if the report was unsure/normal or mild this would be categorized as ‘0’ as this never requires treatment for cardiovascular risk factors. However, if there is a description of moderate or severe WMLs, the report would be categorized as 1 as these cases sometimes require treatment for cardiovascular risk factors.

Included as normal are scattered non-specific foci of signal abnormality (unless a more diffuse or specific pathology is implied) and minor/minimal/mild small vessel disease. Conversely, those cases which are mild to moderate small vessel disease, confluent, or beginning to confluence are treated as abnormal.

- If described as ‘mild to moderate’, then label as MODERATE
- Modest is labelled as mild
- Non-specific white matter dots / foci of signal abnormality, unless a more diffuse or specific pathology is implied, is mild
- Confluencing small vessel disease labelled as moderate to severe
- CADASIL labelled as moderate/severe

A.2 Mass

All the following are categorized as ‘1’ for mass:

- Neoplasms
  - infiltrative tumours
  - extra-axial masses e.g. vestibular schwannoma
  - tumour debulking or partial resection as this includes cavity plus tumor (labelled as both damage and mass)
  - pituitary adenomas
  - ependymal / subependymal / local meningeal enhancement in the context of a history of an aggressive infiltrative tumor
- Abscess
- Cysts
  - retrocerebellar cyst is included but mega cisterna magna is ignored
  - pineal cysts and choroid fissure cysts
  - Including Rathkes cleft cysts
- Focal cortical dysplasia, nodular grey matter heterotopia, subependymal nodules and subcortical tubers
- Lipoma
- Chronic subdural haematoma / hygroma (i.e. CSF equivalent)
- Ignore perivascular spaces unless giant
- Brief surgical planning reports where e.g. GBM was in the indication are labelled as mass
We have attempted to emulate the decision making of a neuroradiologist for all categories. Note that a finding that might generate a referral to a multidisciplinary meeting for clarification would be included within the granular category e.g. an arachnoid cyst may be ignored in clinical practice, but we included it in the ‘mass’ granular category as these are sometimes referred by non-experts to a multidisciplinary meeting for expert review. Thus our classification is sensitive to ensure patient safety.

Examples of mass-like findings considered normal include Thornwaldts cysts and perivascular spaces which are mentioned but where no size indication is given.

A.3 Vascular

All the following are categorized as ‘1’ for vascular:

- Aneurysms
  - including coiled aneurysms regardless of whether there is a residual neck or not
- Arteriovenous malformation
- Arteriovenous dural fistula
- Cavernoma
- Capillary telangiectasia
- Old / non-specific microhaemorrhages
- Petechial haemorrhage
- Developmental venous anomaly
- Venous sinus thrombosis
- Vasculitis if associated with vessel changes such as luminal stenosis or vessel wall enhancement
  - in cases of sluggish flow if strong suspicion of thrombus include otherwise ignore
- Arterial occlusion / flow void abnormality or absence
- Venous sinus tumor invasion (labelled as both vascular and mass)
- Arterial stenosis / attenuation Include if abnormal. If constitutional / normal variant ignore.
- Ignore 3rd ventriculostomy (unless there is a clear description of related parenchymal injury)
- In the context of biopsy, mention if there is obvious damage, otherwise ignore

Note that a finding that might generate a referral to a multidisciplinary meeting for clarification has been within this category e.g. developmental venous anomaly may be ignored in clinical practice, but we included it in the vascular granular category.

Examples of vascular-like findings which are considered normal include descriptions of sluggish flow, flow related signal abnormalities (unless they raise the suspicion of thrombus) and vascular fenestrations.
A.4 Damage

All the following are categorized as ‘1’ for damage:

- Gliosis
- Encephalomalacia
- Cavity
- If the patient has had a craniotomy or biopsy there is likely damage however, for example in the case of a burr-hole and drain previously inserted into the extra-axial space, this does not automatically constitute damage
- Post-operative changes / appearances include as damage
- Tumor debulking or partial resection as this includes cavity plus tumour (labelled as both damage and mass)
- Chronic infarct / sequelae of infarct
- Chronic haemorrhage / sequelae of haemorrhage (with / without hemosiderin staining)
- Cortical laminar necrosis

Examples of damage-like findings which are considered ‘normal’ include craniotomy, burrholes, posterior fossa decompression without complication, and 3rd ventriculostomy

A.5 Acute stroke

All the following are categorized as ‘1’ for acute stroke:

- Acute / subacute infarct (if demonstrating restricted diffusion)
  - Include if there are other descriptors indicating a subacute nature such as swelling or maturing infarct even though restricted diffusion has normalised
- Parenchymal post-operative restricted diffusion / retraction injury (labelled as both ‘damage’ and ‘stroke’)
- Chronic infarct / sequelae of infarct should be labelled under ‘damage’
- If a single event with small diffusion restricting and non-restricting elements then only label as stroke (rather than damage)
- Mature, established or old infarcts without other descriptors should be labelled under damage
- MELAS if associated with restricted diffusion.
- Hypoxic ischemic if associated with restricted diffusion.
- Vasculitis (according to description) if associated with acute / subacute infarct

A.6 Hydrocephalus

All the following are categorized as ‘1’ for hydrocephalus:

- Acute
- Trapped ventricle
- Chronic / stable / improving hydrocephalus (it does not matter whether its compensated or not)
- Ventricular enlargement in the context of atrophy should be ignored and only marked under atrophy
- Include normal pressure hydrocephalus

### A.7 Haemorrhage

All the following are categorized as ‘1’ for haemorrhage:

- Any acute / subacute haemorrhage parenchymal, subarachnoid, subdural, extradural
- Acute microhaemorrhages / petechial haemorrhages should be labelled under haemorrhage. However if its old label as vascular. Acute haemorrhagic foci in the setting of acute axonal injury label as haemorrhage
- When there is old haemorrhagic / blood breakdown products / haemosiderin label as damage
- T1 shortening is likely to represent acute haemorrhage in the immediate post-surgical resection cavity
- Vasculitis if associated with haemorrhage

### A.8 White matter inflammation

All the following are categorized as ‘1’ for white matter inflammation:

- MS and other demyelinating lesions like ADEM and NMO
- MS lesions with cavitation (low T1 signal) - only label as white matter inflammation (no need for additional damage label)
- Research scans that use the phrase No non-MS features are included
- Inflammatory lesions in radiologically isolated syndrome / clinically isolated syndrome
- Focal cortical thinning i.e. subcortical / cortical lesion label as damage
- PML / IRIS
- Leukoencephalopathies - congenital or acquired (including toxic)
- Encephalitis / encephalopathy if it involves the white matter (HIV/CMV)
- PRES
- Osmotic demyelination (central pontine myelinolysis/ extrapontine myelinolysis)
- Susacs
- Radiation if describes white matter abnormality
- White matter changes in the context of vasculitis - only mention if clearly attributed to vasculitis. If non-specific then do not label unless meets other criteria.
- Amyloid-related inflammatory change / inflammatory amyloid
A.9 Foreign body

All the following are categorized as ‘1’ for foreign body:

- Shunts
- Clips
- Coils
- If lots of metalwork was involved e.g. in a cranioplasty (or the occasional craniotomy causing extreme MRI signal distortion)
- If craniotomies are not causing significant artefact, then ignore

A.10 Extracranial

All the following are categorized as ‘1’ for extracranial:

- Total mastoid opacification / middle ear effusions
- Complete opacification / obstruction of the paranasal sinuses
- Ignore mucosal thickening
- If there is clearly a well-defined unambiguous polyp then label as abnormal. If it is ‘retention cysts’ or ‘polypoid mucosal thickening’ then ignore. If it is something indistinguishable which could be a retention cyst / polyp then ignore. Anything leading to obstruction - always label as abnormal.
- Calvarial / extra-calvarial masses
- Osteo-dural defects
- Encephaloceles
- Pseudomeningoceles
- Extracranial vessel abnormality below the petrous segment e.g. cervical ICA dissection
- Lipoma, Sebaceous cyst or any other mass if extracranial
- Orbital abnormalities (including masses)
  - Including optic nerve pathology affecting the orbital segment of the nerve i.e. meningioma
  - If there is an abnormality of the intracranial segment of the optic nerve /chiasm such as atrophy then label as intracranial misc.
- Cases with tortuous optic nerves with no other features are ignored
- Eye prostheses and proptosis
- Ignore pseudophakia
- Bone abnormality e.g. low bone signal secondary to haemoglobinopathy
- Basilar invagination.
- However hyperostosis is considered normal and not labelled (attempting to mirror how a normal radiologist would approach these)
- Thornwalds cysts are ignored
A.11 Intracranial miscellaneous

All the following are categorized as ‘1’ for Intracranial miscellaneous:

- Cerebellar ectopia
- Brain herniation (for example into a craniectomy defect)
- Clear evidence of idiopathic intracranial hypertension (prominent optic nerve sheaths, intrasellar herniation)
  - Non-specific intrasellar arachnoid herniation / empty sella should be otherwise ignored
  - Non-specific tapering of dural venous sinuses should be ignored
- Spontaneous intracranial hypotension (pituitary enlargement, pachymeningeal thickening, etc)
  - If subdural collections present, these should be also noted separately
- Cerebral oedema or reduced CSF spaces
- Absent or hypoplasic structures such as agenesis of the corpus callosum
- Meningeal thickening or enhancement for example in the context of neurosarcoïd or vasculitis
- Enhancing or thickened cranial nerves
- Infective processes primarily involving the meninges or ependyma (i.e. ventriculitis or meningitis)
- Encephalitis if primarily involves the cortex (HSV/autoimmune encephalitis)
- Excessive or unexpected basal ganglia or parenchymal calcification
- Optic neuritis involving the intracranial segments of the optic nerves or chiasmatis
- Adhesions / webs
- Pneumocephalus
- Colpocephaly
- Superficial siderosis
- Ulegyria
- FASIs / UBOs
- Basal ganglia / thalamic changes in the context of metabolic abnormalities
- Neurovascular conflict - if clearly normal, ignore. If clear cut description of neurovascular conflict such as compression or distortion of cranial nerves then label as intracranial misc. If unsure put under REVIEW
- Band heterotopia and polymicrogyria
- Hypophysitis
- Seizure related changes
- ALS (unless there is mention of significant atrophy it may be worth reviewing the images)