more readings

https://zbib.org/4aad92de1d354ceabfe44cbe48efb83f

Ateeq, Tayyab, et al. *Naïve Bayes Classifier Assisted Automated Detection of Cerebral Microbleeds in SWI Brain Images*. Aug. 2023. *tspace.library.utoronto.ca*, https://doi.org/10.1139/bcb-2023-0156.

- random forest achieved 85.7% sensitivity with 4.2 fp/cmb
- naive bayes achieved 90.5% sensitivity with 5.5 fp/cmb
- ⚠ can't find the paper
- based on statistical feature extraction and classification
- method steps
  - removal of the skull and extraction of the brain
  - thresholding for the extraction of initial candidates
  - extracting features and applying classification models such as random forest and naïve Bayes classifiers for the detection of true positive CMBs

Criticism

- Model may have been too simple
- preprocessing may be the defining factor for performance
- threshold for extraction isn't clearly defined

Chen, Hao, et al. "Automatic Detection of Cerebral Microbleeds via Deep Learning Based 3D Feature Representation." *2015 IEEE 12th International Symposium on Biomedical Imaging (ISBI)*, 2015, pp. 764–67. *IEEE Xplore*, https://doi.org/10.1109/ISBI.2015.7163984.

- di ko masyado gets
- extracts features from 2d slices of ground truth and concatenates them to create one volume sample therefore creating a 3d feature representation
- In order to train such a C-NN extractor, 2D slices of ground truth are extracted as the positive samples and negative samples are randomly selected away from ground truths more than 10 mm
- proceeds to classification using the 3d feature representation samples
  - to remove the large number of FP CMBs effectively, a SVM classifier is trained with L2 regularization on proposed 3D feature representation
- **Table 1.** The results of different methods

Method	Sensitivity	Precision	F1-score	Average FPs
RF	0.8696	0.3540	0.5031	14.6
CNN	0.8696	0.3922	0.5405	12.4
Ours	**0.8913**	**0.5616**	**0.6891**	**6.4**

Criticism

- another two-stage approach that uses two-models
- did not use another neural network model for classification but still somehow gave a competitive performance with the other models from previous studies

Fan, Pingping, et al. "Cerebral Microbleed Automatic Detection System Based on the 'Deep Learning.'" *Frontiers in Medicine*, vol. 9, Mar. 2022. *Frontiers*, https://doi.org/10.3389/fmed.2022.807443.

- U-net architecture
- three consecutive layers of slices were used as an input
  - where the middle slice contained the microbleeds for positive samples
- implemented a 3d cnn to extract representative features for complicated CMBs based on the MRI-SWI sequences.
- preprocessing includes scaling global (3d) image intensities and standardization, cropping and resizing to 384x384x3

- used binary cross-entropy loss and the Adam optimizer with an initial learning rate of 10^{-3}
- dice coefficient 0.72
- precision 0.718
- recall 0.765

Criticisms

- similar to the post-processing of a previous study to reduce FPs
- may have needed more slices to the input

Chen, Yicheng, et al. "Toward Automatic Detection of Radiation-Induced Cerebral Microbleeds Using a 3D Deep Residual Network." *Journal of Digital Imaging*, vol. 32, no. 5, Oct. 2019, pp. 766–72. *Springer Link*, https://doi.org/10.1007/s10278-018-0146-z.

- one of the first studies to use deep learning for microbleeds
- simple 3D residual network
- before feeding it into the model, there was an initial detection algorithm that detects initial CMB candidates (set of voxels) that satisfy the predetermined thresholds
  - 2d fast radial symmetry transform on the entire input SWI image volume slice by slice
  - candidate voxels will go through vessel mask screening, 3D region growing, and 2D geometric feature extraction (area, circularity, number of spanned slices, centroid shift distance)
- detection precision of 71.9%

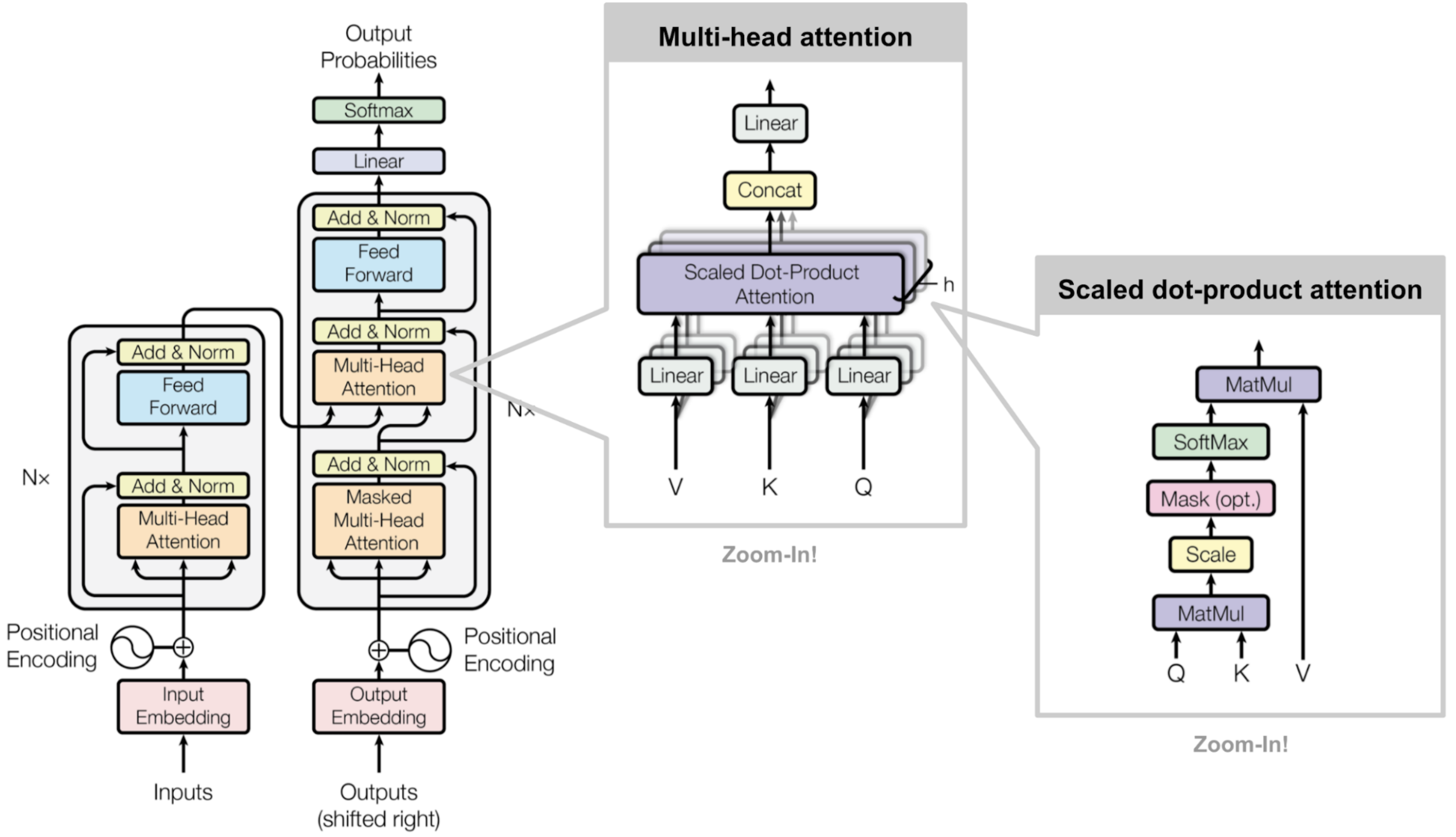
Criticisms

- initial detection algorithm has already been shown to detect 86% of all CMBs
- another feature extraction method

Great article about transformers

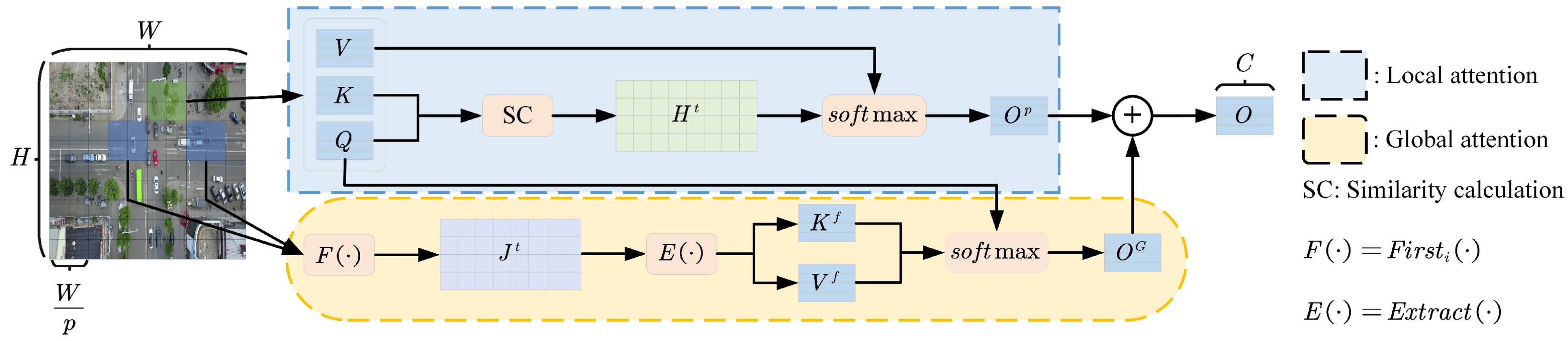
YT vid transformers

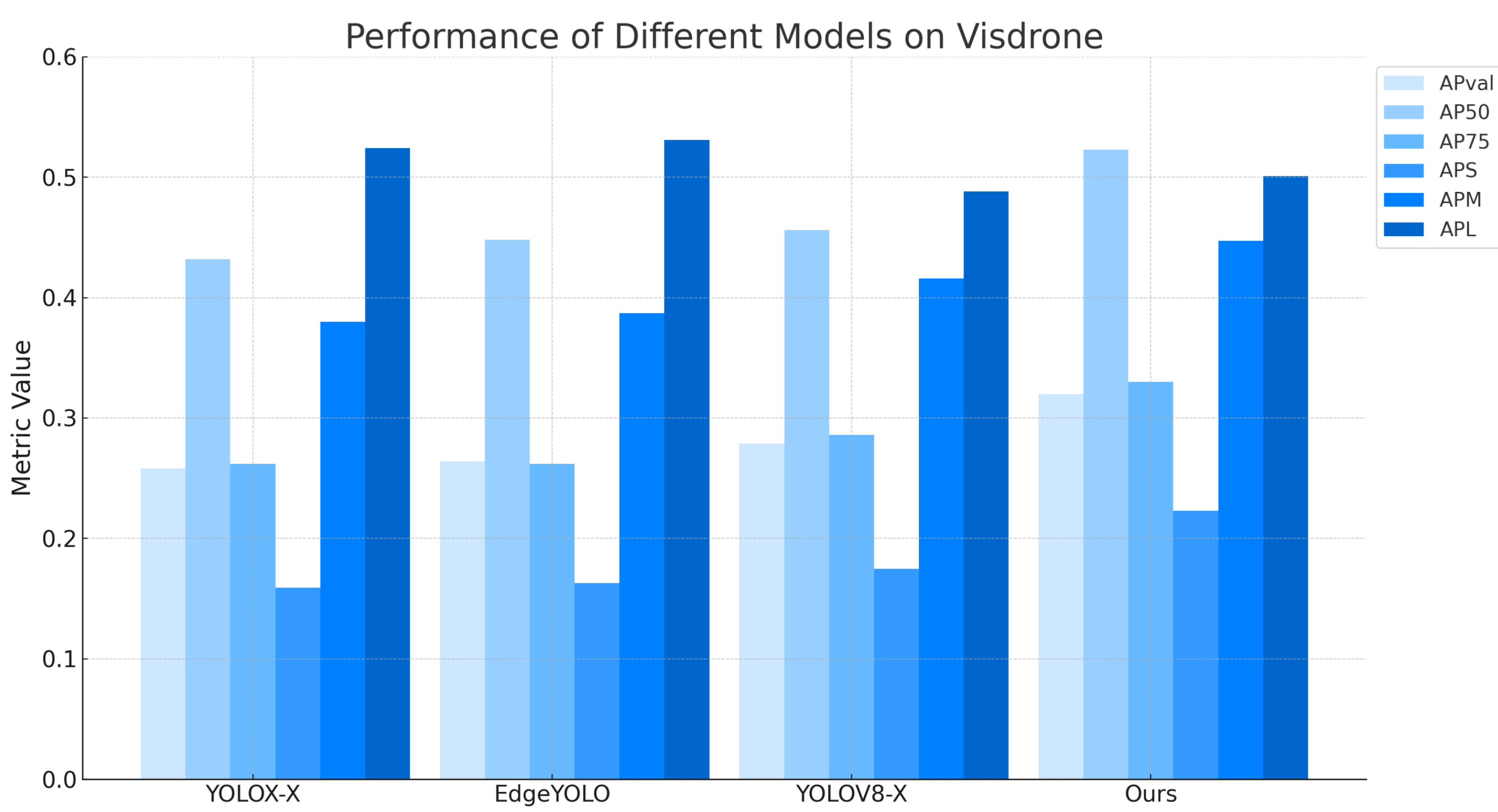
StatQuest YT vid transformers



Li, Yuanyuan, et al. “Remote Sensing Micro-Object Detection under Global and Local Attention Mechanism.” *Remote Sensing*, vol. 16, no. 4, Jan. 2024, p. 644. *www.mdpi.com*, https://doi.org/10.3390/rs16040644.

- In areas like the military, urban planning, and environmental monitoring, the application of remote sensing technology is paramount
- Traditional detection methods are inadequate for effectively detecting small targets,
- used Global and Local Attention Mechanism (GAL)
    - This mechanism, by conducting attention computations at both local and global levels on the input image and applying attention weights to varied windows and key-value pairs, can extract a more profound feature representation
    - Global and Local Attention Mechanism



    - local attention is performed on a partition of the image; a self-attention mechanism it looks like
    - global attention works by selecting the local windows (panes/partitions) that top the similarity score matrix H^t
- Feature Fusion Model: CGAL
    - GAL and convolutional blocks
    - Initially, the module incorporates two CONV blocks with a stride of two, aiming to broaden the receptive field of the network by reducing the spatial dimensions of the feature map. This design ensures that the network comprehensively captures the overarching characteristics of objects, subsequently enhancing their feature extraction capabilities. Following this, the GAL block takes on a central role within the module. Implementing both local and global attention mechanisms, the GAL block delineates the interrelations among input features, producing a refined, weighted feature representation. The module concludes with a CONV block set to a stride of one, a configuration that aids in the preservation of local object features.
- also implemented a new prediction head
- by amalgamating feature maps of different scales from the Backbone network, we can harness the semantic information extracted across multiple scales, effectively capturing the multi-scale attributes of targets.
- 

Criticisms

- why is the global only used the panes that topped the similarity score?
- why not use the attention mechanism on the entire sample
    - if computational costs were the issue it should've been mentioned

Tldr

- Implementation of 3d models are always prepended with an algorithm that always does feature selection/extraction/etc.
- even then, then voxels extracted, or the 3d sizes of the samples seem to be set as hyperparameters
- CMBs might need more contextual information that the limit of the voxel/3d slice may not have been able to acquire