Quantitative Computational Estimation of Liver Steatosis Based on Parameters Derived from Diagnostic Ultrasound

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Abstract

In current medical practice, an ultrasound guided, random needle biopsy of the liver is the gold standard in hepatic steatosis assessment. Ultrasound imaging is used to place a needle into the patient's liver, and extract a core of tissue for pathologist examination. This procedure carries a risk of potentially life threatening bleeding[1], and thus substitution of a needle biopsy with a non-invasive alternative could reduce adverse events. We have developed a machine learning algorithm for analyzing ultrasound (US) images quantitatively to provide computer-aided diagnosis of hepatic steatosis. We built the algorithm using liver US studies from 288 patients, and correlated to their corresponding biopsy assessments. Radiologists identified a region of interest (ROI) on each image which was then filtered for various texture responses. These texture responses formed the parameterization for the machine learning algorithms which, along with the pathology-confirmed diagnoses, were used to train classifiers. Testing with cross-validation, we were able to classify US images as steatotic or normal with sensitivities of 40-74%, and specificities of 72-86%.

Introduction

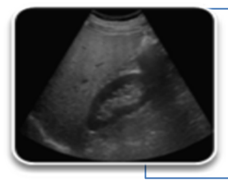
Liver steatosis

- Steatosis is abnormal lipid retention.
- Liver steatosis has a prevalence of approximately 31% in the general population[2].
- While early damage is reversible, long term steatosis can lead to more severe liver conditions such as cirrhosis and liver failure[3].

Previous work in liver US texture analysis

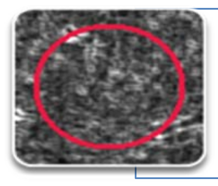
- Livers turn from smooth and dark to coarse and grainy as their fat content increases.
- Fatty tissue has a quantitatively higher echogenicity[4].
- The mean value of the standard deviation of pixel intensities is significantly higher, on average, in patients with chronic liver disease.
- None has reliably diagnosed steatosis based on image texture.

Methods



1. Gather Images
-Retrospectively

2. Choose Region of Interest (ROI)
-Done by Radiologist



3. Parameterize ROIs
-Using the responses from 18 filters

4. Train and Cross Validate
-Using Support Vector Machines and Random Forest algorithms

Results

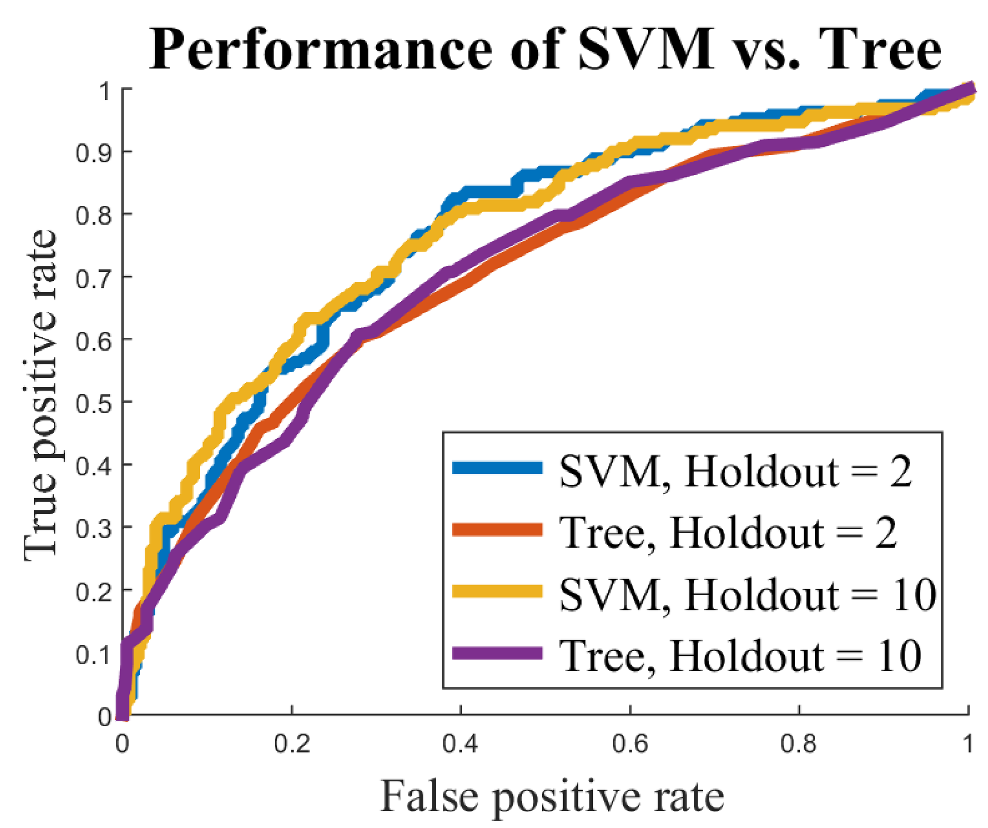


Figure 1: The receiver-operating curves of support Vector machines (SVMs) and random forest (Tree) algorithms in classifying steatotic liver US. Cross-validation holdouts of 2 and 10 were used. SVMs were consistently superior to Tree; the holdout value made very little difference.

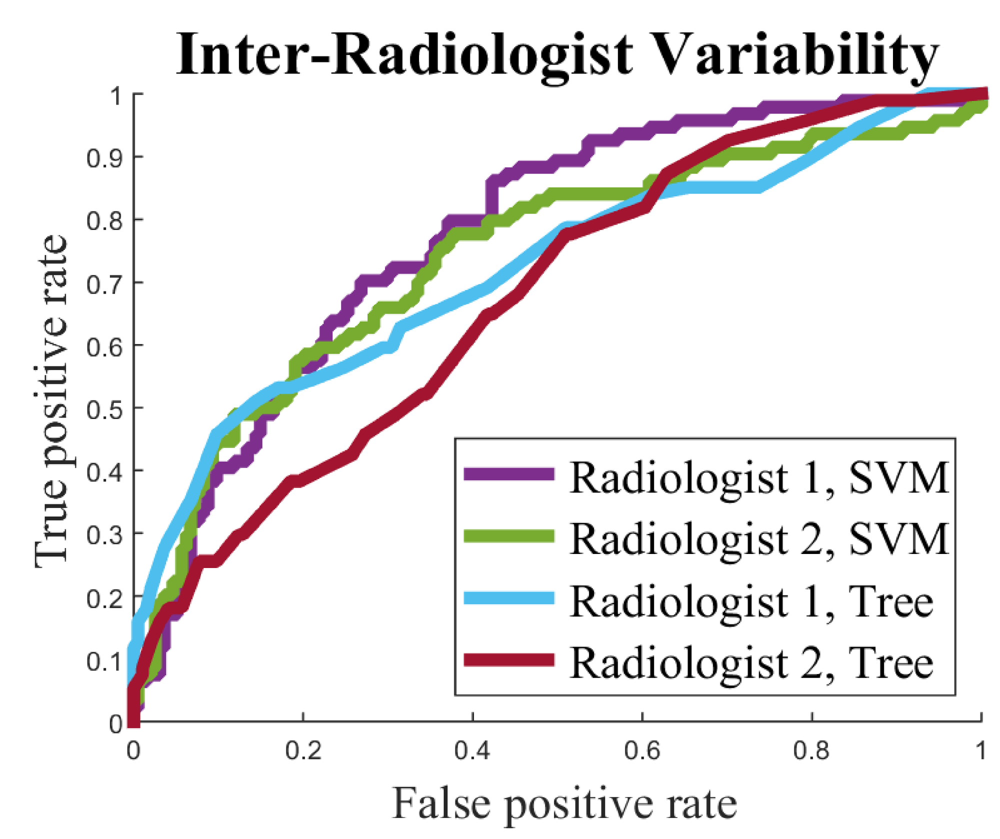
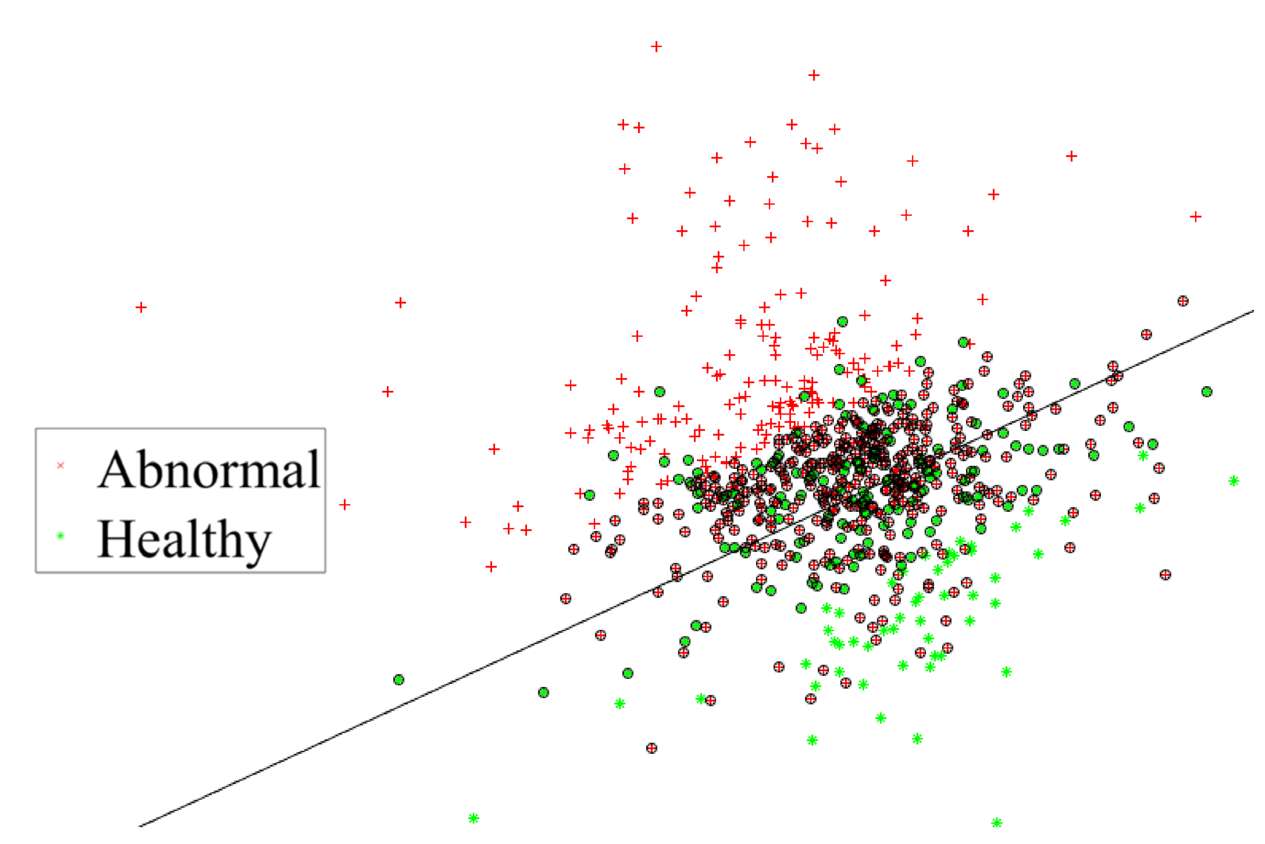


Figure 2: A comparison of the performance of machine learning algorithms when trained on different radiologists' ROIs. Algorithms trained using the ROIs from Radiologist 1 generally, though not always, outperformed those trained using the ROIs from Radiologist 2.

Figure 3 (Right): A two dimensional representation of the 36 dimensional space in which the support vector machine places its hyperplane decision boundary. In order to reduce the dimensionality, principle component analysis was used. The red icons, representing the abnormal steototic livers, are more abundant above the decision boundary. The green icons, representing livers without significant steatosis, are more abundant below the decision line. Red icons below the line, or green icons above, represent images that were misclassified by the algorithm.



Classifier, hold-out set size	Sensitivity	95% CI (%)		Specificity	95% CI (%)		+LR	C-Stat	95% CI		P-Value
Steatosis											
SVM, 2	74%	[68	79]	72%	[67	77]	2.66	0.71	[0.67	0.74]	<.0001
SVM, 10	71%	[64	77]	73%	[68	78]	2.61	0.70	[0.66	0.74]	<.0001
Tree, 2	40%	[33	48]	86%	[82	89]	2.90	0.67	[0.62	0.71]	<.0001
Tree, 10	47%	[39	55]	85%	[82	88]	3.19	0.69	[0.64	0.73]	<.0001

Figure 4 (Left): The performance and statistical analysis of the classifiers. SVMs substantially outperformed Tree algorithms on the metric of sensitivity, but were outmatched in specificity. These values, however, only represent one point on each's respective receiver-operating curve.

Conclusions

- Machine Learning techniques can be used to inform clinical decision making in liver steatosis
- Support vector machines are mildly more effective than random forests in classifying liver US images
- Our algorithm is resistant but not entirely insensitive to changes in ROI selection from radiologist to radiologist

Future Directions

- Incorporate a greater number of texture filters
- Incorporate other parameters, such as relative echogenicities of liver and kidney
- Develop a protocol for more rigorously standardizing the ROI selection process, thereby reducing inter-operator differences

References

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Acknowledgments

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