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Imaging Biomarkers in Young Patients With ADPKD

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INTRODUCTION

The development and continued expansion of numerous cysts in the kidneys is an invariant feature of autosomal dominant polycystic kidney disease (ADPKD). Baseline height corrected total kidney volume (HtTKV) assessed by magnetic resonance imaging (MRI) and age has emerged as an imaging biomarker for estimation of disease progression in adult patients and is the basis of the Mayo classification system.[1] However, predicting prognosis in children is more complex. Despite the presence of cysts in the kidneys of young patients with ADPKD, kidney function may remain normal for many years. Therefore, HtTKV is the best indicator of disease severity for young patients. Recently an adult study showed that the addition of MRI texture features improved prognostic value over HtTKV alone.[2] Therefore, the objective of this study was to explore whether additional MRI features extracted from baseline kidney images improved prediction of disease progression beyond baseline HtTKV alone in young patients with ADPKD.

RESULTS

The goal of this investigation was to determine whether inclusion of additional baseline imaging features assessed by MRI would improve the fast progression group prediction over that obtained with baseline HtTKV alone. Seventy-one young patients were determined to have suitable images collected at baseline and after 3 years.[3] Among these, 37 (mean age 14.5 ± 3.6 years, 46% male) met the criterion for fast progression based on annual percent increase in HtTKV > median of 7.4% and 34 (mean age 15.9 ± 3.9 years, 27% male) slow progression. All patients had normal kidney function. When using only baseline HtTKV to predict fast kidney disease progression, the mean area under the curve (AUC) was 0.56 and the F1 score 0.49 (Table 1).[S1] Next, the baseline imaging features were analyzed in combination with HtTKV based on a forward search of the features with transformation and inclusion of the principal components for each type of feature (see Supplementary Methods).[4–9] The best result was obtained with the model that included Gabor and GCLM features in addition to HtTKV. This resulted in an increase in AUC to 0.70 and a mean F1 of 0.71 as shown in Table 2. Addition of geometric, intensity-based texture, and local binary pattern features in combination with HtTKV did not improve the AUC value (mean AUC 0.65 and F1 of 0.50). Likewise, the analysis of feature transformation and principal components of the baseline feature without inclusion of HtTKV yielded a poorer discrimination of progression group in terms of AUC and F1. The best model for the latter analysis included Gabor features alone with an AUC of 0.64 and F1 of 0.65. A central kidney image was used for all analyses. However, similar analysis of adjacent kidney images significantly correlated with data for the central image (Supplementary Table S1).[S2,S3]

Table 1. Prediction results for kidney disease progression in autosomal dominant polycystic kidney disease using baseline HtTKV

Cross Validation							
HtTKV	1	2	3	4	5	Mean	SD
Accuracy	0.50	0.36	0.50	0.50	0.50	0.62	0.11
Precision	0.44	0.25	0.75	0.45	0.83	0.55	0.21
Recall	0.67	0.14	0.33	0.83	0.55	0.51	0.24
F1	0.53	0.18	0.46	0.59	0.67	0.49	0.17
AUC	0.52	0.54	0.53	0.53	0.64	0.56	

AUC, area under the curve; HtTKV, height corrected total kidney volume.

DISCUSSION

In adult patients with ADPKD, baseline HtTKV in conjunction with age separates patients into classes predictive of decline in eGFR.[1] However, no similar classification is available for children with ADPKD. Prediction of kidney disease progression in young patients with ADPKD is difficult. Kidney function is typically preserved in childhood and may be further complicated by the occurrence of hyperfiltration. Therefore, HtTKV remains as the best predictor for more severe disease and faster disease progression. In this study, we examined whether additional extracted features from MRI imaging could improve prediction of the rate of kidney growth (fast vs. slow progression) over measurement of baseline HtTKV alone. We found that baseline HtTKV alone resulted in an AUC value of 0.56. This may be lower than expected due to the small sample size. However, when HtTKV was combined with Gabor and GLCM features the AUC increased to 0.7. Furthermore, principal components analysis improved the prediction in the overall study.

A main limitation of this pilot study was the number of cases available for analysis. Only 71 patients had suitable imaging data collected at baseline and after 3 years. However, the results obtained from this study merit repetition in larger cohort with a longer follow-up period.

In conclusion, this result indicates that a combination of imaging features may be a better predictor of disease progression assessed by rate of increase in HtTKV in young patients with ADPKD.

Table 2. Prediction results for kidney disease progression in ADPKD using baseline HtTKV plus principal components of transformed baseline features

Cross Validation							
HtTKV + Gabor + GLCM	1	2	2	4	5	Mean	SD
Accuracy	0.50	0.79	0.79	0.64	0.73	0.69	0.11
Precision	0.44	0.70	0.87	0.57	0.86	0.69	0.16
Recall	0.67	1.00	0.78	0.67	0.67	0.76	0.13
F1	0.53	0.82	0.82	0.61	0.75	0.71	0.12
AUC	0.60	0.83	0.89	0.60	0.70	0.70	

ADPKD, autosomal dominant polycystic kidney disease; AUC, area under the curve; GLCM, gray level co-occurrence level; HtTKV, height corrected total kidney volume. AUC is calculated based on the average receiver operating characteristic (ROC) curve of the 5-fold cross validation models.

DISCLOSURE

All the authors have declared no competing interests.

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SUPPLEMENTARY MATERIAL

Supplementary File (PDF)

Supplementary Methods.

Supplementary Reference.

Table S1. Similarities between extracted features in adjacent kidney magnetic resonance images.

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