Automatic Scoring of Shulman's Clock Drawing Dementia Test

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Abstract: With dementia currently being one of the biggest healthcare challenges, an improvement in diagnosis represents a substantial improvement for the patients and medical experts. A frequently used diagnosis tool is the clock drawing test (CDT), cognitive short test typically conducted with pencil and paper and manually scored by a medical professional. This paper introduces a transparent approach for software-assisted scoring and screening of CDT, using a combination of deep learning elements and standard image recognition techniques. Unlike an end-to-end approach, our strategy involves dividing the process into distinct subprocesses. This division ensures that intermediate results are readily available throughout, establishing a robust and transparent foundation for the diagnostic process. A dataset containing 1236 CDT-scans is used for evaluating our algorithm's ability to score the result into a category from 1 to 6 and the ability to classify *pass* or *fail* is assessed. Based on the results a component-wise software-assisted approach to CDT scoring seems to be a viable alternative to end-to-end systems.

1 INTRODUCTION

Dementia is one of the biggest healthcare challenges in out society affected by global ageing, with more than 55.2 million people worldwide suffering from it in 2019 and up to 139 million estimated cases in 2050 (World Health Organization, 2021).

It is a syndrome consisting of symptoms like cognitive impairment, mood and behavioral changes. These symptoms can be caused by several diseases, namely Alzheimer's disease, vascular dementia resulting from a stroke and Lewy bodies. Abusive use of alcohol or an unhealthy lifestyle can promote the development of dementia. (World Health Organization, 2023)

In Germany it is recommended to diagnose dementia in two steps: *Base diagnosis* where the patients medical history is recorded and cognitive short tests are conducted. One commonly used short test is the so-called clock drawing test with an evaluation scheme proposed by psychiatrist Shulman (Shulman et al., 1986). Following the base diagnosis, the next step, known as the *differential diagnosis*, involves investigating the severity and underlying causes through further medical examinations (DGPPN, 2017).

Although previous attempts to automatically evaluate the clock drawing test using end-to-end deep learning (DL) approaches have shown promising results, these methodologies often lack transparency and explainability in their decision-making processes. This limitation poses a significant impediment to their practical application within the domain of diagnostics (Holzinger et al., 2019). Consequently, the primary objective of this study is to divide the CDT into transparent subproblems presented to the medical expert by applying a hybrid approach incorporating deep learning and image recognition techniques, while trying to achieve high accuracy in evaluating the clock drawing test. The feasibility is evaluated based on a reference dataset of scans, including the ground truth scores provided by medical experts (Chen et al., 2020).

This paper is structured as follows: We discuss the clock drawing test in section 2 and summarize the underlying image recognition methods in section 3. After that, we introduce the scoring algorithm in section 4, which is evaluated using the real-world dataset presented in section 5 and the corresponding metrics in section 6. In section 7, the experimental results of evaluating of our algorithm's ability to score and classify a CDT-scan as *pass* or *fail* are presented, followed by a discussion in section 8. Finally, we provide a summary of our findings and an outlook on improvements and further research in section 9.

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2 CLOCK DRAWING TEST

The clock drawing test (CDT) is a valuable tool in dementia diagnosis, due to the fact that it involves multiple cognitive functions and behaviors. In this assessment, patients are instructed to complete a given circle so that it resembles a clock face, and then draw clock hands indicating the time '11:10'. Subsequently, a trained professional assigns a score ranging from 1 to 6, with categories 1 and 2 denoting *pass* and categories 3 to 6 *fail*.

According to Shulman, this test offers several advantages that make it an effective instrument for cognitive screening (Shulman, 2000). Alongside other cognitive short tests, for example the Mini-Mental-Status test (MMST), the task engages various cognitive functions, including abstract thinking, visual memory, motor skills, and hand-eye coordination. The execution of the task provides insight into a patient's capacity to cope with frustration and challenges. Moreover, the test is cost-effective, easy to administer, and independent of speech or educational background. Siu et al. (Siu, 1991) reported a high likelihood ratio of 24 (7.5-74) for an abnormal result in the clock drawing test, indicating that an unfavorable test outcome allows for conclusions on the patient's cognitive state.

Nonetheless, practical application challenges have been noted by Chen et al. (Chen et al., 2020). These challenges include difficulties in getting appointments with specialists, high inter-rater variability, and potential biases that human raters may develop with respect to a patient's appearance, status, or family background. These limitations emphasize the need for software-assisted scoring to mitigate potential issues in the test's evaluation.

There are multiple kinds of scoring systems commonly used for the CDT, among those are the Sunderland (Sunderland et al., 1989) and the Agrell (Agrell and Dehlin, 1998) schemes. This study uses the Shulman scheme as it is often applied in dementia diagnosis in Germany. Furthermore the experimental CDT data was created and prelabeled with respect to the Shulman scheme.

3 IMAGE RECOGNITION

In the following, we briefly revisit the essential image analysis techniques which form building blocks for our image recognition pipeline. Specifically, the Hough transformations for line and circle detection. Other techniques applied in the algorithm are standard intensity-based segmentation, providing linked edge-points forming contours and Gaussian blur-filtering for filling gaps in the contours.

The Hough transformation is used to detect simple geometrical shapes in images. First of all, geometrical shapes such as lines or circles can be described by a set parameters. To determine the parameters describing the shapes a so-called Hough-space can be created. An edge detection is applied to compute all points resembling an edge. For every edge point a set of lines that pass through the point is calculated. After all edge points are processed, a peak detection process determines the set of parameters corresponding to parameters of the shapes. (Gonzalez and Woods, 2018)

4 SCORING ALGORITHM

The algorithm contains four processing stages.

(i) preprocessing

(ii) digit recognition

(iii) clock hand recognition

(iv) final scoring

The input consists of a CDT-result scan and the algorithm's output is an ordinal score from 1 to 6 and a *pass* or *fail* classification.

The initial preprocessing step for a CDT-scan consists of clock face identification using Hough transformation for circle detection. Subsequently, the scan is cropped to simplify the analysis process. The preprocessing stage produces three distinct outputs: one featuring thickened lines designed for clock hand detection, another one with gaps filled using Gaussian filtering, facilitating continuous contour detection in digit recognition. Additionally, a cropped variant is generated to provide feedback during the evaluation phase

In the initial phase of digit recognition, a contour detection process is employed to identify and extract all contours within the image using an algorithm that returns connected edge points as a contour (Suzuki et al., 1985). The identified contours are subsequently pre-sorted based on criteria such as size, aspect ratio, and proximity to the center of the image in order to identify potential digit candidates. Following this preliminary selection, the contours are cropped from the original image and these extracted images are classified utilizing a model trained on the MNIST dataset [1] of handwritten digits, that can accurately classify inputs into the range of digits from 0 to 9. Post-classification, further processing is done to identify double-digit sequences (ranging from 10 to 12) by

[1] http://yann.lecun.com/exdb/mnist/

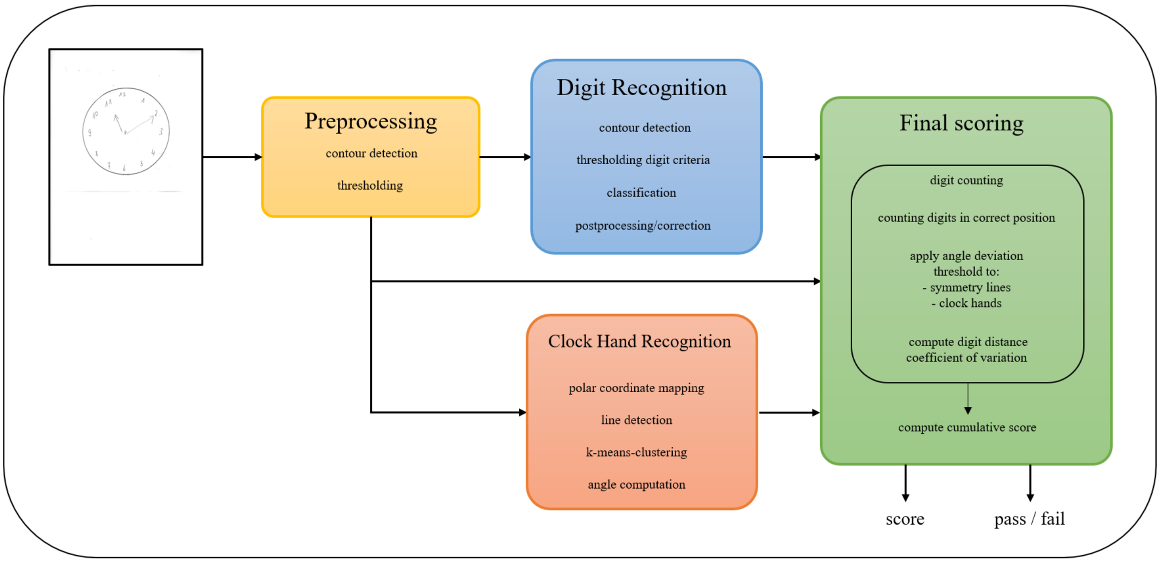


Figure 1: Schematic representation of the CDT-scoring algorithm.

evaluating the proximity between contours classified as 0, 1, or 2. Additionally, certain classifications will be corrected based on their position on the clock face. For instance, misclassifying a '1' as a '7' can be corrected, as there is no digit that resembles a '7' in the upper half of the clock. The digit classification model is a simple convolutional neural network (CNN) with three convolution-pooling blocks and several processing layers, accepting a 28×28 input and capable of classifying inputs into the range of digits from 0 to 9.

For clock hand recognition, the preprocessed image is mapped into a Cartesian coordinate system using a polar coordinate transform. Subsequently, a Hough transformation, specialized for line detection, is applied. The output of this transformation is then filtered to identify horizontal lines, given that the polar coordinate mapping tends to represent lines radiating from the center as horizontal lines. The y-coordinates of the extracted horizontal lines are subjected to clustering via the k-means algorithm. This clustering process, with parameter k set to 2, identifies two centroids, which, in turn, allows for the precise calculation of the two clock hands' angles.

In the process of *scoring*, all subtask outputs, derived from clock hand recognition and digit recognition, are combined and used for computing a final overall score based on a set of established scoring criteria designed for the clock drawing test. This comprehensive evaluation encompasses various aspects: First, from the digit recognition component, key parameters are considered, including the total count of correctly identified digits, the number of digits accurately positioned (as depicted in Figure 2), the presence of both vertical and horizontal symmetry lines, as well as the alignment with the reference lines corresponding to the hour and minute clock hands. It is noteworthy that suitable criteria for symmetry, clock hand angles, and distance variation coefficient have been derived from a preparatory study and are delineated in Table 1. Additionally, the variation coefficient for the spacing between the digits (v) is computed as part of the scoring process, where a $v \leq 0.295$ is rated as perfect and $0.295 < v \leq 0.44$ is rated as okay. Each of these criteria is assigned a specific number of points, contributing to an overall cumulative score, i.e. all individual scores are added together. Notably, special emphasis is placed on the evaluation of the clock hands, as their absence or inaccuracies serve as crucial indicators or features for high point ratings within the scoring system.

Table 1: Angle deviation thresholds for the scoring criteria clock hands and symmetry lines.

Criteria	Δα Perfect	Δα Okay
Clock hand	±30.0°	±45.0°
Vertical line	±7.5°	±15.0°
Horizontal line	±20.0°	±40.0°

Finally, an overall score is computed as the output of the analysis process. It is important to emphasize that, due to splitting the process and the utilization of predetermined criteria for decision-making, the scoring process ensures a high level of transparency. Preliminary outputs are accessible at every stage of the process, promoting clarity and facilitating a more

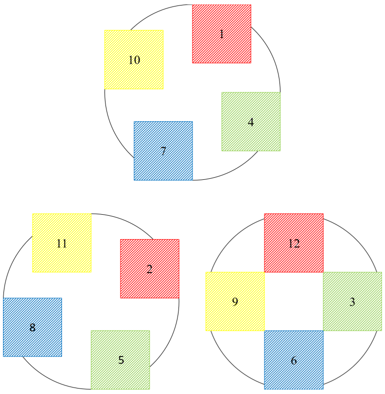


Figure 2: These figures illustrate the valid ranges for the positions of the digits." The height and width of the boxes each make up one third of the clock's diameter. The colors are for illustration purposes only and have no scoring impact.

thorough understanding of the assessment. Moreover, the performance of individual sub-tasks can be assessed and compared to optimize the complete algorithm's output.

5 DATA

The dataset used to test and develop the algorithm was collected by (Chen et al., 2020) for developing an end-to-end deep learning based approach to CDT-scoring. It contains 1393 scans of results produced by patients conducting the clock drawing test in the Shulman system. The data was collected from July 2018 on in the clinic for neurology in Nürnberg, Germany. Within this dataset, the average age is 69 ± 14.7 years with 58.1 % are male and 41.9 % female patients.

The images are assigned into six categories on an ordinal scale (1-6), where categories 1 and 2 are considered as *pass* and categories 3-6 as *fail*, by medical experts as ground truth. Additionally, there are 46 images in a validation folder. After reviewing the dataset, 11.27 % clocks were removed across all categories because they contained contours outside the given circle. Due to the design of the algorithm proposed in this paper, with scans being cropped to the given circle, a valuation of these clocks is not intended. The remaining subset of the data contains 1236 clocks across all six categories. Sample diagnostic drawings for all six categories can be found in (Chen et al., 2020).

6 EVALUATION METRICS

The underlying problem of assigning scores 1 to 6 to CDT-scans is an ordinal regression problem (OR), whereas the problem of categorizing scans into *pass* or *fail* can be considered a straightforward binary classification problem. In the following, we discuss appropriate evaluation metrics for both settings.

Ordinal Regression involves classifying an object into one of several ordered classes, denoted as Y, subject a distinct ordered structure: $Y = \langle y_1 \prec \ldots \prec y_n \rangle$. Notably, despite the prevalence of ordinal regression in computer science, there is no consensus on how it should be evaluated (Baccianella et al., 2009). A widely employed metric is the mean absolute error (MAE), which calculates the differences between a classification and its corresponding ground truth across all elements (n) within a given category:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \qquad (1)$$

Baccianella et. al (2009) advocate for the adoption of the macroaveraged mean absolute error (MAE^M) in the context of imbalanced datasets. This metric ensures that each prediction contributes equal weight in the evaluation process, mitigating the impact of class imbalance. To calculate the macroaveraged MAE, the MAE of every category is computed and divided by the number of categories (C):

$$MAE^M = \frac{1}{C}\sum_{i=1}^{C} MAE_i \qquad (2)$$

For the evaluation of the screening component, we consider the application of well-established metrics, specifically accuracy, precision, recall, and the F1-score. Additionally, in the evaluation of screening, scoring, and the digit recognition process, confusion matrices are computed to provide a fine-grained prediction representation.

7 RESULTS

The experimental results were computed using the real-world dataset introduced in section 5. The result assesses the performance of the algorithm explained in section 4. Three subcomponents of the algorithm are evaluated: Assigning a score to a CDT-scan (*scoring*) is an ordinal regression problem and examining how well the algorithm distinguishes between *pass* and *fail* (*screening*) is evaluated using binary metrics. To get a better understanding of possible underlying issues in approach, the subprocess "digit recognition"

Table 2: Result of the evaluation of digit recognition. The evaluation is conducted using digits from the clock dataset and the MNIST dataset. The classification accuracy before and after position correction (PC) was calculated for each category. Additionally, the percentage of discarded digits is reported.

dataset	score	accuracy - w/o PC [%]	accuracy - PC [%]	discarded digits [%]	digits
CDT-scan digits	1	93.17	96.10	9.21	226
	2	88.94	95.48	9.13	219
	3	84.0	88.94	20.95	253
	4	83.3	83.41	24.12	286
	5	83.2	80.8	39.81	211
	6	82.14	82.14	76.6	120
	1-6	89.64	89.31	28.37	1195
MNIST		99.35	/	0	10000

is evaluated separately. This evaluation is of crucial importance, as the results of digit recognition serve as the foundation for both the scoring and screening processes.

7.1 Model Performance on Clock Digits

The model's digit classification performance is assessed by extending the original dataset and labeling digits originating from 15 CDT-scans across all categories and evaluating the model's prediction performance before and after position correction (cf. digit recognition in section 4) is applied. Contours, that don't resemble a digit, and still passed the criteria described in section 4, were sorted out in the labeling-process, as the model is only capable of predicting digits from 0 to 9.

On the extended subdataset the digit classification model yields an accuracy of 89.64 % across all digits and scores. With the best accuracy in categories 1 and 2 with 93.17 % and 88.94 %, and intermediate results in categories 3 to 6 with an accuracy of around 83.3 %.

Regarding the position correction, this processing step has a positive effect on the classification accuracy for digits in clock scans from categories 1 to 3, while it has a negative or no effect in categories 4 to 6, which makes sense, as these categories are typically characterized by the absence of a normal clock structure.

We have observed that several contours (digit candidates) that are not actual digits are incorrectly classified as a digit and have a negative impact on the evaluation. If they are taken into consideration, the overall accuracy evaluatesto 70.79 % before, and to 72.71 % after position correction. The best prediction performance is achieved for digits originating from clocks with score 1, and the worst accuracy in category 6 digits with 19.17 % since 76.6 % of the contours were excluded or removed.

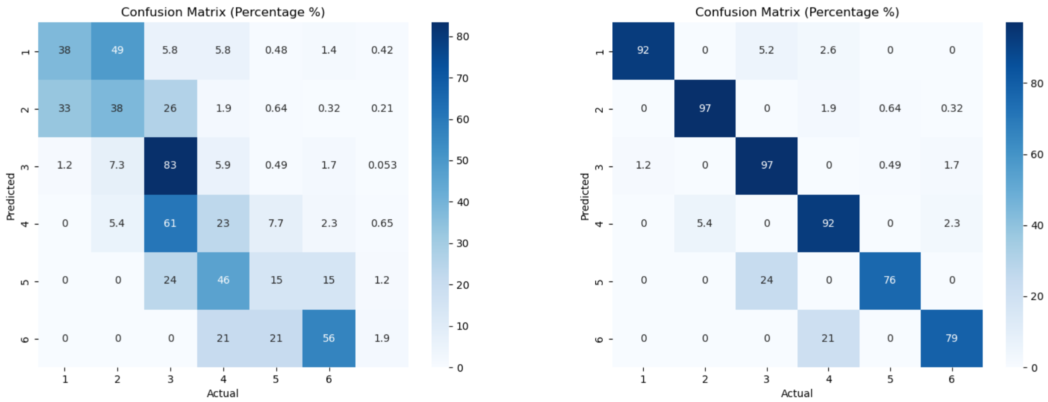
7.2 Scoring

The scoring process pertains to an ordinal classification regression, and its evaluation is based on the mean absolute error (MAE), as expounded in section 6. Therefore, the mean absolute error of the classification outcomes within each category is calculated for the considered dataset. Table 3 presents the obtained evaluation results. Notably, a minimal MAE of 0.2171 characterizes the classification of score 3 as the most accurate, whereas scores 5 and 6 exhibit MAE values close to 1.1. On average, the dataset yields a MAE of 0.7209. It is essential to emphasize that the mean absolute error approximates 1, further reinforced by an off-diagonal confusion matrix (Figure 3b) for classification (Chen et al., 2020). This matrix accounts for cases where misclassifications differing by a single unit only from the correct classification are considered as correct. Furthermore, a detailed representation of the scoring performance is provided through the confusion matrix, as depicted in Figure 3a, which offers insights into the clock drawing test scoring process.

Comparing the two confusion matrices, it is apparent that the result with confusion matrix 3a having a accuracy for correctly classifying a CDT-scan into the categories 1 to 6 of only 51.46 % and 93.47% from the off-diagonal 3b. Showing there are inaccuracies that need to be solved.

Table 3: Mean-Absolute-Error per score and macroaveraged Mean-Absolute-Error across all scores.

score	MAE
1	0.8738
2	0.6624
3	0.2171
4	0.8450
5	1.0909
6	1.0606
$MAE^M(1-6)$	0.7209



(a) CDT-scoring results (b) off-diagonal CDT-scoring results

Figure 3: Normalized confusion matrix depiction of the scoring result, presented in percentages [%]. Confusion matrix (a) shows the raw scoring outputs and (b) shows an off-diagonal representation of the results, where misclassifications, that are off by one unit are considered correctly classified.

7.3 Screening

Evaluating the algorithm’s capability to decide if a CDT-result is considered *pass* and *fail* leads to the results in Table 4 and Figure 4. To facilitate this evaluation, the classifications for categories 1 and 2 are merged, and similarly, the classifications for categories 3 to 6 are combined, effectively establishing the binary *pass* and *fail* classes for analysis. The algorithm classifies the CDT-scans with an accuracy of 87.31 %. The precision amounts to 85.35 %, whereas the recall amounts to 93.64 %, indicating a high level of accuracy for correctly classifying negative result as such.

Table 4: Results of screening. The accuracy [%], precision [%], recall [%] and F1-score are computed.

Accuracy	Precision	Recall	F1-Score
87.31	85.35	93.64	0.8931

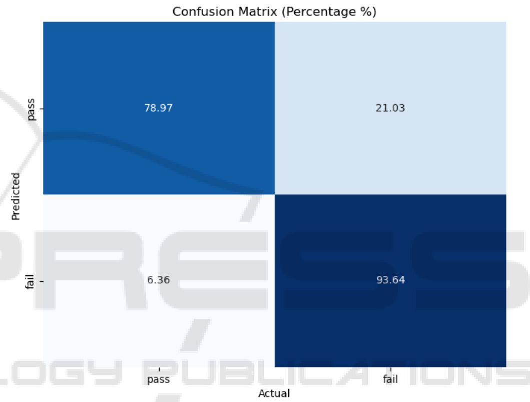


Figure 4: Normalized confusion matrix depiction of the screening result, presented in percentages [%].

8 DISCUSSION

Our empirical results show that it is possible to evaluate results of the clock drawing test using the Shulman scoring scheme with the transparent component-wise approach of combining image recognition techniques and deep learning.

It is evident that the pure multiclass classification performance with a low classification accuracy of 51 % is neither satisfactory nor robust. The confusion matrix in Figure 3b, shows potential for achieving better results with improved subtask prediction performance. In this discussion, we will investigate potential sources of inaccuracy and errors, and explore potential counter corrective measures that could ultimately enhance the accuracy and effectiveness of both the scoring and screening processes.

The primary source of inaccuracy most likely stems from using a deep learning model for digit recognition, which is only capable of classifying digits from 0 to 9. Classifying double-digits is a challenge handled by a heuristic digit preprocessing. A conceptual issues poses the input of non-digit contours and the incorrect classification as digit between 0 and 9, because the model is only capable of classifying between 0 and 9. This has a negative effect on the whole final scoring of the CDT scan and the basis of all scoring aspects. Firstly, the model’s output contains the number of digits and can also have an impact on counting the digits, that are in the correct position (criteria in scoring), since non-digits inputs are often simple lines misclassified as ’1’. Additionally, the digit recognition output serves as the reference for determining symmetry lines. These lines are calculated based on the centers of the topmost and bottommost digits for vertical symmetry and the leftmost and rightmost digits for horizontal symmetry. Furthermore, it impacts the distance variation coefficient as artifacts or additional lines are frequently unevenly distributed across the scan. Lastly, for instances where the algorithm identifies a 2 and an 11 it uses their centers as references for calculating the optimal angle for the clock hand evaluation. Therefore, the accuracy and reliability of the digit recognition component significantly influence the entire CDT scoring process.

Another critical aspect regarding the digit classification model is that it is trained using data from the MNIST dataset and subsequently applied to classify digits within CDT-scans without further transfer learning on these specific digits. The handwritten digits in the MNIST dataset, were mostly created by young American highschool students and employees of the National Institute for Standards and Technology, whereas the scans were conducted in Germany. This raises the possibility that there are differences how Americans and Germans write digits. Also people suffering from dementia are typically older, another aspect distinguishing the clock digits from the training data.

Another potential difference between the ground truth and model's prediction could stem from the discretion that a human rater can perform case-by-case decisions. It is possible for a medical expert to assign a perfect rating to clock hands that are drawn as a direct line between 2 and 11 without touching the center the clock face, as it is clear that the patient correctly identifies the correct time. Our detection algorithm on the other hand is not capable of doing that, as it is looking for lines originating in the center of the clock, which might not always align with human evaluative criteria.

Reevaluating the exact criteria for the final scoring within the algorithm might be necessary on a technological level to provide both transparent and accurate predictions in scoring. However a thorough study by Mainland et al. (2014) implies that, in the medical context, it is more important to correctly assess between *pass* or *fail*, than to increase the complexity of scoring criteria, to depict the cognitive state a person. (Mainland et al., 2014).

Our algorithm evaluates a scan of CDT result, performed on paper with a pen. Information about the patients behaviour and the time taken for completing the test is lost in this form of evaluation.

To conclude this discussion there are some inaccuracies in the current algorithm, especially regarding the digit recognition. However the results show the potential of an automatic evaluation of the CDT, especially when it comes to binary classification as *pass* and *fail*.

9 CONCLUSION

This paper examines the feasibility of scoring and screening the clock drawing test with a transparent, component-wise approach of combining traditional image detection methods and deep learning. The proposed algorithm yields good prediction accuracy for screening, where a CDT-scan is classified as *pass* or *fail*. Especially in correctly classifying true-negative results, which is of particular relevance in practical dementia diagnosis, only 6.36 % of failed CDT-scans are misclassified as *pass*.

The MAE from scoring and the confusion matrices in Figure 3 suggest that there are some issues in precise ordinal regression prediction. However incorrect predictions are off by a score of 1 and resolving the issues discussed in section 8 could lead to improvements of the accuracy.

Future advancements of the algorithm should prioritize more precise digit recognition, such as the implementation of a non-digit-class for input training. Moreover, it is imperative to engage in a comprehensive review and standardization of the digital scoring criteria, involving a multidisciplinary team of experts encompassing the fields of dementia, neurology, clock drawing testing and computer science. This collaborative effort will ensure that the scoring criteria are transparent, robust and universally accepted.

Part of the preparatory work has been creating an app[2] for digitally performing the clock drawing test on an iPad. The result is scored with a variant of the algorithm, described in this paper and showed good results, that are of clinical significance.

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