Automation of motor dexterity assessment

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Abstract— **Motor dexterity assessment is regularly performed in rehabilitation wards to establish patient status and automatization for such routinary task is sought. A system for automatizing the assessment of motor dexterity based on the Fugl-Meyer scale and with loose restrictions on sensing technologies is presented. The system consists of two main elements: 1) A data representation that abstracts the low level information obtained from a variety of sensors, into a highly separable low dimensionality encoding employing t-distributed Stochastic Neighbourhood Embedding, and, 2) central to this communication, a multi-label classifier that boosts classification rates by exploiting the fact that the classes corresponding to the individual exercises are naturally organized as a network. Depending on the targeted therapeutic movement class labels i.e. exercises scores, are highly correlated -patients who perform well in one, tends to perform well in related exercises-; and critically no node can be used as proxy of others -an exercise does not encode the information of other exercises. Over data from a cohort of 20 patients, the novel classifier outperforms classical Naive Bayes, random forest and variants of support vector machines (ANOVA: $p < 0.001$). The novel multi-label classification strategy fulfills an automatic system for motor dexterity assessment, with implications for lessening therapist's workloads, reducing healthcare costs and providing support for home-based virtual rehabilitation and telerehabilitation alternatives.**

I. Introduction

Following brain damage originated by stroke, brain trauma or palsy among others, the surviving patient is often left with a range of impairments -restriction of body functions- and its consequences -limited activities and restricted social participation- [17] including motor impairment. Motor impairment may result in muscle weakness, poor stamina, lack of muscle control or total paralysis, interfering with activities of daily living and thus degrading the quality of living of the patient. Motor rehabilitation refers to physical -targeting recovery of gross motor skills- or occupational -targeting fine motor control and recovery of activities- therapies aiming at increasing the patient participation and daily activities by improving function and minimize development of secondary problems [18]. During rehabilitation, the clinical team routinely estimates the patient progress evaluating changes in her motor dexterity. This assessment is carried out by administrating some tests and establishing motor recovery through clinically validated scales such as the Fugl-Meyer scale [11]. A number of different clinical evaluation scales appraise related but distinct constructs about motor recovery, including dexterity. Motor dexterity assessment is thus a regular task performed by the therapists.

The automation of the motor dexterity assessment may alleviate the workload burden of therapists during in-ward sessions and collaterally reduce treatment costs for both the healthcare system and the patient. In addition, this automation is a necessary step towards fully enabling information technologies-based variants of occupational therapy such as virtual rehabilitation [15], in which therapeutic exercises are disguised as serious computer games; and telerehabilitation [16], where exercises are delivered outward at the patient's residence via internet.

Given the demand for automating motor dexterity assessment, the goal of this research is thus to build a system that can automatically perform the dexterity assessment based upon the Fugl-Meyer scale. Since the system has to work both on hospitals alleviating therapists' schedule, and at homes supporting home-based rehabilitation, the sensing requirements have to be flexible to adapt to different scenarios. The problem hence involves two stages; first, finding a suitable data representation dictating the ability of the system to cope with different sensing scenarios, and second, a classification stage that actually resolves the assessment problem by matching the patient exhibited performance to its associated scale outcome.

Finding a suitable data representation requires transforming raw data from different sensing geometries to a common abstract data representation that encodes body positioning, so this representation can be capitalized upon to follow a single analysis path to discern motor assessment. In essence, this is a manifold embedding problem and a vast range of projection functions are available in the literature including principal component analysis (PCA) [24], Isomap [25] or t-distributed Stochastic Neighborhood Embedding (t-SNE) [4] among many others. Following experimental testing reported in [29], we chose t-SNE to achieve the representation that we found to be the most beneficial for subsequent classification in this particular problem. The building of the representation is very briefly described in Sect. II-A.

This paper focuses on detailing our solution proposal for the second stage of the problem, that of classifying motor exercise performance that effectively affords the automation of motor dexterity assessment. Since the Fugl-Mayer scale requires the execution of several exercises, the classification stage is naturally seen as a multi-label classification problem whereby each exercise of the test represents a different label. Multi-label classifiers are multivalued functions linking observations to N class labels [1]–[3]. Existing multi-label classification (MC) perspectives can be coarsely divided into

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label power-set methods and binary relevance methods [5]. The former approaches create classifiers for all possible combinations of labels but suffer from high computational burden. The latter build individual classifiers per class ignoring any information about class interaction if existent. In between, intermediate approaches maintain one classifier per class but informing classifiers of outcomes resolved earlier, thus fully or partially harnessing class interaction information e.g. [6], ideally getting the best of both worlds. These intermediate approaches vary in the way they pass resolved information to late resolved classifiers, from the most simple list-like chain [9], to sophisticated hierarchical or tree-like [3], [19] and network-based chain [6], [13] strategies. Bayesian chain classifiers. model the class dependencies as a bayesian network, and based on this structurebuild the chain using the labels of the parents This circumstance matches that of the problem of motor dexterity assessment and its convenient automation that we are addressing here.

Our hypothesis, when building our solution, is then that since parents might not be reliable representative of their ancestors, relaxing the assumption of proxy-parents and permitting any ancestors' labels to reach their descendants classifiers, shall result in an improvement in the classification rates in scenarios such as the automatic assessment of motor dexterity aforedescribed. Although we have previously hinted this possibility of allowing the ancestors labels to reach subsequent classifiers [19], this is the first time we implement and validate this strategy. We further contribute here with a feature selection step resolved by means of full model selection, which we are not aware to have been anticipated before in multi-label classification, and which is critical to support the hypothesis as it will be shown. The proposed solution is trialed on a dataset captured during clinical assessment of motor dexterity of patients undergoing motor rehabilitation, and shown to improve classification rates over more simplistic classifiers.

A. The Fugl-Meyer Assessment (FMA)

Motor dexterity assessment evaluates, through clinically validated scales, the ability of a patient to perform specific movements related to how a healthy individual would have, on average, performed such movement. Perhaps the most widely used scale for the assessment of motor dexterity is the Fugl-Meyer scale [11]. During the Fugl-Meyer assessment (FMA) the patient executes a sequence of exercises which are scored by the therapist to quantify the exhibited dexterity. The FMA consists of several blocks of exercises, and for assessment of the upper limb, only a subset of exercises forming one of these blocks from the full FMA scale are used. These are summarized in Table I, and some of these exercises are illustrated in Figure 1. Each exercise is scored on a 3-point ordinal scale; 0 (absence of movement), 1 (clearly impaired movement) or 2 (healthy-like movement), and the final score is just the sum of all scores for the individual exercises.

TABLE I: FMA exercises for the upper extremity.

#ID	Exercise	Simplified Instructions
a)	Extension Flexion (hand)	With the elbow touching the side, and forearm pointing forward move thew affected hand up and down as if waving
b)	Extension	Move affected hand from the same side knee to to the opposite knee and back.
c)	Flexor Synergy	Move affected hand from the opposite knee and to same side ear pointing the elbow outwards.
d)	Extensor Synergy	Move affected hand from a lateral hanging position to the opposite knee without moving the trunk.
e)	Combined Synergy	Move affected hand from the same side knee to the lower back.
f)	Combined Synergy	Move affected hand from a lateral hanging position upwards to 90 degree (pointing to the horizon) without flexing the elbow.
g)	Pronation Supina-tion(hand)	With elbow touching the side, and the forearm pointing forward rotate the affected hand (palm up $\rightarrow$ palm down)
h)	Shoulder Ab-duction 90	Move affected hand from a lateral hanging position sideways to 90 degree.
i)	Shoulder Flexion	Move affected hand from pointing at the hori-zon upwards 180 degree (reach up).
j)	Coordination/ Speed	Move the index finger of the affected hand from the opposite side knee to nose (5 repe-titions as fast as possible)

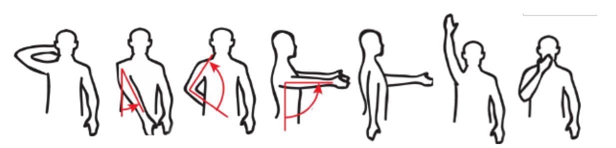


Fig. 1: Subset of upper extremity Fugl-Meyer exercises.

II. Methodology

A. Abstract data representation common to multiple sensing geometries

Two sensing configurations were considered to demonstrate the ability to escape a fix sensing geometry: (i) 3-dimensional (3D) rotation, traslation, orientation was acquired from inertial measurement units (IMU), and (ii) 3D rotation and traslation was retrieved for each skeleton segment estimated by the Kinect using OpenNI implementation for person detection. The raw signals vary between the sensors and are not a good representation for classification purposes [28].

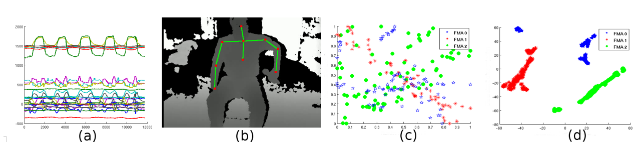


Fig. 2: Data-flow. a) Raw sensor data S, b) Orientation space (schematic depiction alike a skeleton) f, c) Normalized orientations g, d) Projection to salient component space using t-SNE h. Illustrated data correspond to data collected during a previous pilot on healthy subjects.

An abstract representation is obtained by transforming data to a common space as we have previously reported [22], [23]. This representation is a function composition $R = h \circ g \circ f(S)$

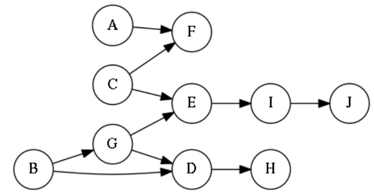
projecting the raw signal S first to an orientation space f, normalizes the rotations g, and finally projects to a space of salient components (h) with high class separability by means of t-SNE [4] (see Fig: 2).

B. Chained multi-label classifiers

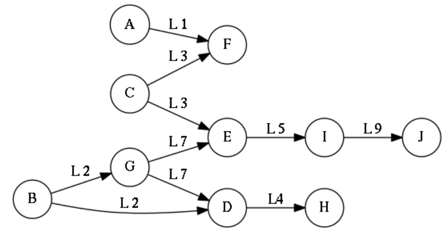
Let X_n denote observations and $C = \{C^i\}$ a set of classes with $c_k^i \in C^i$ the k-th label of the i-th class. In MC, the aim is to assign a vector of labels $c = \{c_k^i\}$ with $i \geq 1$ to a certain observation X_n. This requires the definition of a multi-valued classification model from observations to label sets $f : X \rightarrow c$. Often the goal is to find a projection f with high predictive power as characterized by some acceptable trade-off among type I and II errors. Such projection f can be split into a collection of simpler single-valued $f_i : X \rightarrow c^i$. Each f_i can benefit from knowing the decision of previously solved f_js, $f_i : X \times c'(i) \rightarrow c^i$ with $c'(i) = \{c_k^j \mid j \neq i\} \subset c$ a subset of previously resolved decisions, with the critical question of deciding the best subset $c'(i)$ for each f_i. In simple list-like chain classifiers, classes C^i are assigned a mathematical relation of order $R_<$ and $c'(i) = \{c_k^j \mid j \neq i \wedge R_<\}$, with the ordering being critical as any c_k^j depends on the evaluation of its predecessors in $R_<$. In network-based classifiers, leaf classifiers -the earliest to be evaluated- do not have parents i.e. $c'(i) = \{\emptyset\}$, whereas for other nodes $c'(i) = \{c_k^j \mid j = 1 \ldots N, j \neq i\}$ such that $c'(i) \cap c'(j) = \emptyset$, that is $c'(i)$ is only left to contain its direct parents labels'. Note how the chain is implicitly encoded in the $c'(i)$s. Upon definition of the class dependency network C', current approaches will limit $c'(i) = \{Pa(c^i)\}$ where $Pa(\bullet)$ indicates the parents of a node, assuming the class C^i as a suitable proxy of all preceding ancestors.

C. Augmentation of the network-based chain multi-label classifiers with ancestors

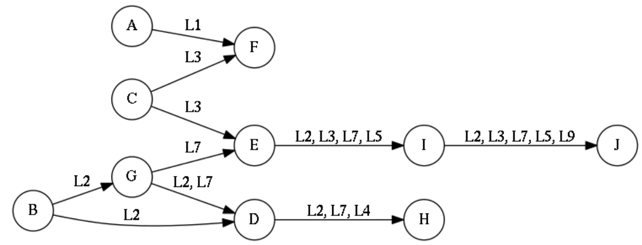
1) Extending network-based chain classifiers to accept ancestors: Our proposal starts by permitting a more flexible definition of $c'(i)$ whereby $c'(i) = \{c_k^j \mid j = 1 \ldots N, j \neq i\}$ but the constraint $c'(i) \cap c'(j) = \emptyset$ is dropped thus permitting the incorporation into the current decision of decisions taken by previous ancestors other than just parents. In the problem of motor dexterity assessment, the classes C^i correspond to the subset of exercises of the FMA scale for the evaluation of the motor dexterity in the upper limb summarized in Table I. In this case, because of the domain application, we depart from an acyclic graph defining the class dependency network structure fixed a priori by a domain expert (LRC) and graphically illustrated in Fig 3a. However, the rationale of the newly proposed ancestor-enriched chain classifier does not depend on whether the class structure is automatically learned as in the case of Bayesian network-based chain classifiers [6] or given. Regular network-based chain classifiers use only the output label of the direct parent classes as features as shown in Fig: 3b. This new ancestor-enriched variant illustrated in Fig.3c allows the classifier f_i to exploit information from any ancestor.



(a) Original class dependency network defined by an expert



(b) Simple network-based label chaining; only labels from parents are passed as features to child classifiers.



(c) Incorporating elders to the label chaining; all preceding classifier labels are forwarded as candidate features to subsequent classifiers.

Fig. 3: Class dependency structure for the Fugl-Meyer exercises for the assessment of the upper limb, and strategies for label passing.

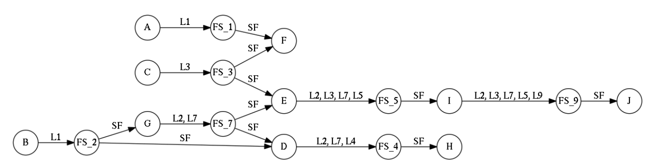


Fig. 4: Feature selection per classifier using Particle Swarm Model Selection (with fixed SVM classifier).

2) Selection of appropriate ancestors; optimizing $c'(i)$: By default, the new chaining use all ancestors' labels as additional features. Not all additional candidate features c_k^j available for classifier f_i may convey interesting information to help the classification C^i. Thus, a filtering stage, implemented by means of feature selection techniques, is added to optimize $c'(i)$ as depicted in Fig: 4. The feature selection strategy is based on Particle Swarm Model Selection (PSMS) [7] to select the best performing features of each individual classifier considering only SVM classifiers. The fixing of the classifier in the PSMS only affects feature selection, and not the classifier themselves or parameters. Although full model selection is possible (maybe even beneficial), its use is unrelated to the contribution expressed in this work and thus it is intentionally restricted here. This decision reduces the computational burden of the simulations.

III. Experiments and Results

A. Experiment set up

Data was obtained from 20 consenting patients suffering motor impairment in their upper limb of different etiology undergoing motor rehabilitation at four different rehabilitation centers from Mexico. Cohort demographics is presented in Table II. The participants were assessed by a trained clinician (LRC) for motor dexterity of their upper limb using the Fugl-Meyer scale.

All 20 patients completed the 10 evaluation exercises corresponding to the FMA subset for the upper extremity and their total scores are indicated in Table II. Snapshots of the experimental session are pictured in Fig: 5.

TABLE II: Cohort demographics. FMA indicates the total score which is the sum of the individual scores across all exercises. Hand.: Handedness, Aff.: Affected side

Subj.	Gender	Condition	FMA	Hand.	Aff.
1	Male	Trauma	1	Right	Right
2	Male	Stroke	5	Left	Right
3	Female	Stroke	16	Right	Left
4	Male	Trauma	19	Right	Left
5	Female	Stroke	52	Left	Right
6	Male	Trauma	13	Right	Right
7	Male	Stroke	0	Right	Left
8	Female	Stroke	0	Right	Right
9	Male	Trauma	25	Right	Right
10	Male	Stroke	53	Right	Right
11	Female	Stroke	32	Left	Right
12	Male	Stroke	12	Right	Left
13	Male	Stroke	60	Right	Right
14	Female	Trauma	5	Right	Left
15	Male	Stroke	3	Left	Right
16	Male	Stroke	53	Right	Right
17	Female	Stroke	32	Right	Left
18	Male	Stroke	12	Right	Right
19	Male	Stroke	60	Right	Right
20	Female	Stroke	5	Left	Left

Fig. 5: Experimental sessions. Patients executing the Fugl Meyer exercises. A trained clinician (not in the image) was assessing their dexterity while the sensors acquired data. Patients faces have been blurried for blinding.

During the assessment by the human expert, the patient's upper limb kinematics was concurrently being monitored at 60 Hz with (i) an IMU (LPSM-B from LP-Research, China) placed on the upper arm of the affected side and (ii) a Kinect sensor (Microsoft, USA) placed at approximately 2m in front of the patient at a height of 85cm on a fixed tripode.

B. Analysis

The individual scores given by the evaluating expert were accepted as the ground truth. The Fugl-Meyer Assessment (FMA) [11] exhibits high reliability [10]. Because of this reliability, there is only need for one expert to give the scores for the ground truth. An expert physiotherapist (LRC) manually fixated the network of dependencies among the different exercises, as shown in Fig 3c

The experimental dataset was used to train a series of ten -one per exercise- Support Vector Machine(SVM) [8] classifiers with a radial basis function kernel that scored (classified) the corresponding exercises independently. Optimization of the feature selection stage implemented with PSMS was guided by accuracy(=(TP+TN)/(TP+TN+FP+FN))[1]. Each of the proposed methods was also used to train a sets of ten SVM chained classifiers with a radial based function kernel.

A leave one subject out replication strategy was used for validation purposes. Comparison is established against paradigmatic independent classifiers (IC) -which makes no use of class interaction-, a naive list-like chain classifier (LLC) -which does not exploit the hierarchical structure of the classes, and a baseline graph-like single parent-based chain (SLC) -for which the class structure assumes that parents labels encapsulate all previous classification exercises-. In addition, for our ancestor augmented proposal, both intermediate values -not exploiting feature selection (MLC)- and the final values -exploiting feature selection (FS-MLC)- are reported. Primary endpoint was classifier accuracy. Statistical analysis of significance was established using one way ANOVA followed by post-hoc pairwise Tukey comparison.

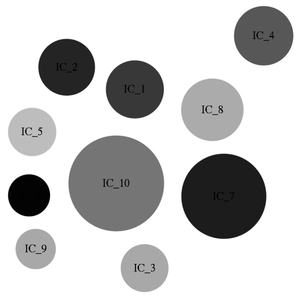
C. Results

The effectiveness of the common representation to abstract the sensing geometry and pave the way for classification is exemplified in Fig: 6. Table III summarizes average accuracy and standard deviation of classifiers. The methods using MLLC surpased the acurracy of LLC and SLLC by a statisticaly significant range $P < 0.05$. In addition the proposed FS-MLC method shows, an average increment in accuracy of 3.8 and a std reduction of 0.45 compared to MLLC. This difference was statistically significant $P < 0.001$ using a Wilcoxon-Mann-Whitney Test compared to MLLC indicating that the use of feature selection for each exercise independently generates an immediate improvement in classification.

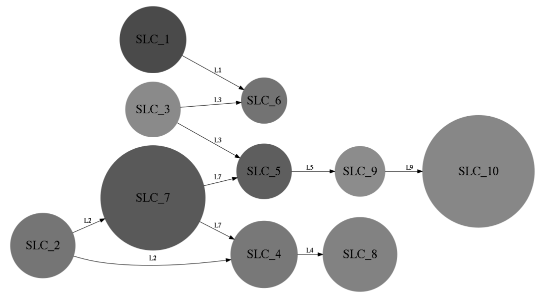
D. Discussion

Several efforts have been made towards providing an automatic solution to this problem [12], [20], [21] but thus far the reported success rates (maximum reported accuracy: 87.3%) [30], translating into 44.65 correspondence with clinician opinion) are insufficient to guarantee wide clinical

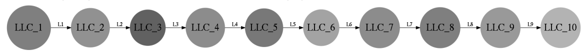
[1]TP: True positives; TN: True negatives; FP: False Positives; FN: False negatives.



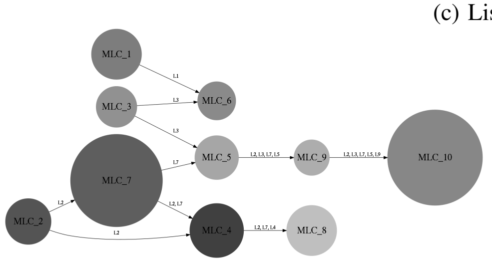
(a) Independent classifiers (IC)



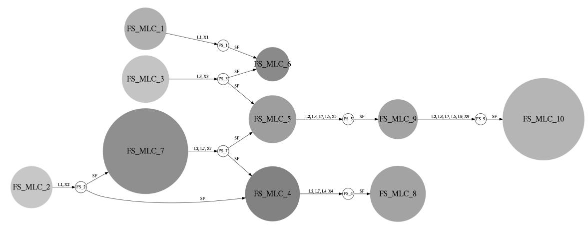
(b) Classical network-based chaining (using only parents) (SLC)



(c) List-like chaining (LLC)



(d) Ancestor-enriched network-based chaining (MLC)



(e) Filtered ancestor-enriched network-based chaining (FS-MLC)

Fig. 7: Flow of predictive power (as expressed by accuracy) across classifiers. The circle radius is proportional to the average accuracy reach by the classifier. The shade of gray represents scaled standard deviation (black = higher deviation; white=lower). This representation suggests how each classifier improves its chances of higher prediction rates as it taps on previously made decisions and how the different strategies of building $c'(i)$ affects the uncertainty in the classification process.

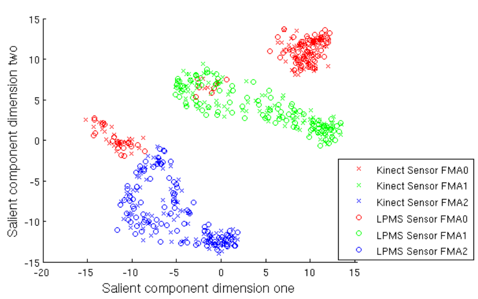


Fig. 6: Projection of experimental data from the different sensing geometries to the common abstract representation for one of the Fugl-Meyer exercises. It can be appreciated how the data from equal performances map to similar regions of the space regardless of the different generative sensing strategy.

acceptance. Our hypothesis in this regard is that if we can increase classification rates of motor dexterity exercises by capitalizing on information shared among classes, then the technology will come closer to acceptance by clinicians. As the results suggest, the average classification benefits from the relaxation of the assumption that parent nodes encode all previous information and critically from the feature selection stage. As the early classifiers provide their decisions to the subsequent classifier, the output appears to reduce its uncertainty in the sense that there is a decreasing trend in

TABLE III: Comparison of accuracy (mean±STD) across different classifier methods on a leave one out validation.

Classifier	**Accuracy Mean $\pm$ STD**
Naive Bayes	68.08 $\pm$ 7.97
Random Forest	79.12 $\pm$ 11.54
Lineal SVM	69.95 $\pm$ 10.65
Radial SVM	79.53 $\pm$ 6.93
PSMS	82.94 $\pm$ 4.94
LLC	84.62 $\pm$ 5.82
SLLC	85.34 $\pm$ 2.84
MLLC	89.85 $\pm$ 3.20
FS-MLLC	93.65 $\pm$ 2.75

the standard deviation (see Fig: 7). Also, an interesting detail to highlight, is that the early classifiers do not yet show the improvement that their child's exhibit permitting the SLC approach to exhibit a non-significant higher accuracy for the first two classifiers.

IV. Conclusions and Future Work

We have presented a novel classification strategy to realize the automatic assessment of motor dexterity, a problem which despite its potential impact remains unresolved from the point of view of clinical acceptance. The system is based on a novel network-based chain multi-label classifier enriched with a critical feature selection step. The success of the contribution (higher predictive power against tested alternatives) appears to capitalize on the optimal selection of the ancestors labels. Despite the improved accuracy, we consider that there is still work ahead before a clinically acceptable automatic alternative to human expert conducted assessment of motor dexterity will be available.

The findings are limited by the small sample size and uncorrected unbalance in class labels, but the results suffice to suggest the feasibility of the approach. The unaggressive processing and the inexpensive optimization used makes us believe that there is margin for improvement. Also, we have not reported on how the achieved classification rates translates to reliability as compared to different experts. Although as indicated, FMA enjoys high reliability, this does not equate to all clinicians reaching the same score when blind to each other. If an automated system is to be clinically accepted, it does have to afford maximal accuracy rates to an accepted experiment specific ground truth, but to actually show an inter-rater reliability comparable to that of other human experts.

As future work we consider exploring network-based chain MC with a per class full model selection approach using not only the best features for each class but also the optimized classifier to provide a classification that exploit the mutual information while locally optimizing each individual classifier, and attending the necessity to achieve inter-rater reliability to levels of human experts.

Acknowledgments

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