Predicting difficulty of an Endodontic Case using Neural Networks

Problem statement

Endodontic treatments act as a successful conservative treatment plan in several cases. But, it can fail due to multiple reasons that a general dentist is unable to foresee before initiating the treatment or due to conditions that may not be controllable by the dentist. This often leads to retreatment, referral to an endodontist or extraction of the tooth. In order to avoid such failures, prompt referral of the case to an endodontist is required after assessing the case. Machine Learning (ML) is becoming the new frontier of technological advancements in dentistry. Predictive algorithms have been employed in various domains to come to the aid of experts in the said domain. Utilizing the American Association of Endodontists' (AAE) Endodontic Case Difficulty Assessment Form, which is a standard used to assess an endodontic case, ML algorithms are proposed to make a decision whether the case should be referred to an endodontist before initiating the treatment.

Introduction

The most important part of any successful dental procedure is careful diagnosis and treatment planning. Through proper assessment of a case, a dentist recognises the difficulties associated with the successful treatment of the case, and understands the risk of an inadvertent failure of the case can be prevented by referral to a specialist. A poor case selection leads to an endodontic failure. Dentists usually rely on clinical evaluations, radiographs and their experience for treatment planning of an endodontic case. Often a clinician faces a dilemma whether referral to an endodontist is required or not. The American Association of Endodontists (AAE) Case Difficulty Assessment Form is a standard form used to collect data related to a case, which makes it possible to misdiagnose and mistreat a patient. It allows a dentist to perform proper case selection-based upon his or her skills, experience and comfort level. In this manner, cases that are beyond the experience and comfort level of a general dentist can be referred to an endodontist to manage the patient's endodontic needs and assure delivery of effective endodontic care.

Technology has proven to be a boon in various domains of medical treatment. Machine Learning, is a domain that aims at building self-learning algorithms, which can improve with experience. It has been finding a large number of applications in medical treatment since its inception, to assist the physician in diagnosis. The general principle about learning in terms of medical treatment is, to collect diagnostic knowledge from the previous cases, apply it on new patients to assist the physician and increase speed of diagnostic phase. Machine is becoming a new frontier for use of technology in dentistry. Primarily, in the diagnostic phase to reinforce decisions of a dentist, to train students and to aid non-specialist dentists. In this study, Machine Learning algorithms are fed with patient records collected using the AAE Case Difficulty Assessment Form along with an expert's decision for each record concerning the referral of the patient to a specialist. The algorithm learns from the given data and derives a classifier which can be used to make decisions for new patients in future. Machine Learning algorithms are predictive and have a level of accuracy associated with its predictive quality. Even though the

accuracy may not have a perfect score, they do give acceptable results provided the training was done using quality data and correct algorithm was selected based on the type of features found in the data.

Dataset

The dataset used in this study has been acquired from Nair Hospital Dental College's Endodontics Department with the approval of the ethics committee. It is a set of anonymous records of root canal patients' pre-treatment assessments along with a tag whether they were referred to a specialist or not. The dataset is realized from the AAE form by considering each question on the form as a feature, making it 17 features. The columns are given weights as per its severity to finally sum up and get a numeric value for each of the 17 features, as listed

Features

- 1. Medical History
- 2. Anesthesia
- 3. Patient Disposition
- 4. Ability to open mouth
- 5. Gag reflex
- 6. Emergency condition
- 7. Diagnosis
- 8. Radiographic difficulties
- 9. Position in the arch
- 10. Tooth isolation
- 11. Crown morphology
- 12. Canal and root morphology
- 13. Radiographic appearance of canal(s)
- 14. Resorption
- 15. Trauma history
- 16. Endodontic treatment history
- 17. Periodontal-Endodontic condition

Target

1. Refer to specialist or not

The dataset contains 324 instances and it will be split randomly into 80-20% to generate training and test set. The dataset contains no missing values.

Tools and Algorithms

TensorFlow

TensorFlow is an open source Machine Learning API available majorly for Python and Go. It provides a vast number of complex calculation APIs and canned ML algorithms to use and takes care of the optimization of the calculations to produce results as fast as possible. TensorFlow can be installed for Python using **pip**, the Python package manager.

```
pip install tensorflow
```

TensorFlow has the ability to take advantage of GPU if present on a system. To do so, TensorFlow binary has to built from its source code openly available on GitHub, the build is dependent on **Bazel** which runs on Linux and Darwin operating systems. Running TensorFlow on GPU increases the speed of training by many folds.

TensorFlow can be used for Inference/ Prediction in Java. To export a TensorFlow model so as to use it in Java or any of the supported languages, the canned ML algorithm estimators give a predefined function. The model gets saved as a graph along with information about the variables in the graph. In Java, training is not possible so it would be a good practice to make this model constant (freezed). Freezing a model converts all variables into constants and gives a single graph file which for most of the cases is very compact, rarely penetrating into the MegaByte values.

DNNClassifier

This is one the available canned estimators in TensorFlow which provides a high level of abstraction with respect to its internal working. Even so, the network created is highly configurable. A DNNClassifier is basically a fully connected neural network with zero or more possible hidden layers. The activation functions, and optimization algorithms can be chosen from a wide variety. It handles the pain of saving checkpoints and model graphs automatically during the training and utilizes them on retraining by default.

Our network has an input layer with 17 input features and the output layer has one neuron making binary classifications. There are two hidden layers each with 5 neurons.

The hidden layers use the ReLU activation function which is given by

```
f(x) = x^+ = \max(0, x)
```

The function basically makes all negative inputs as zero and keeps positive inputs as is. So the range of output will be [0,inf)

The optimization algorithm used to minimize the loss function is Adagrad Optimizer which is known to be best suitable for Neural Networks. Initial learning rate fed to the optimizer was 0.1 and Adagrad Optimizer reduces the learning rate as it closes into a minima while optimizing.

Learning happens over epochs inside a deep neural network when error is back propagated to adjust the weights of connections between neurons of adjacent layers. Our algorithm uses 1000

epochs over the training set and is analyzed for accuracy over the blind test set. The learning happens over mini batches of input data, the batch size used in this model is 128.

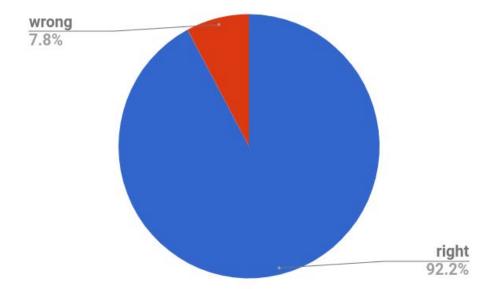
Android

The GUI of our application is built as an Android app using Java which is fed with the frozen model graph. It provides the same AAE form as an interface to make predictions for future patients. Patient information is sensitive and this application cannot be used for fun, hence security is taken into consideration and a Firebase powered backend regulates authorized access to the form and the ML model.

Analysis

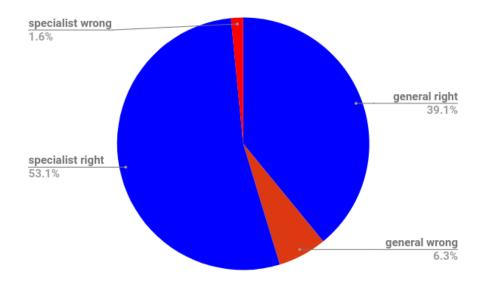
Accuracy

The accuracy achieved by our neural network can be observed in the following graph. The graphs were prepared from results obtained over the blind test set which can be a good approximation for unseen future patients. Since the dataset is split randomly each time training happens, the accuracy changes in the range of 89%-96%.

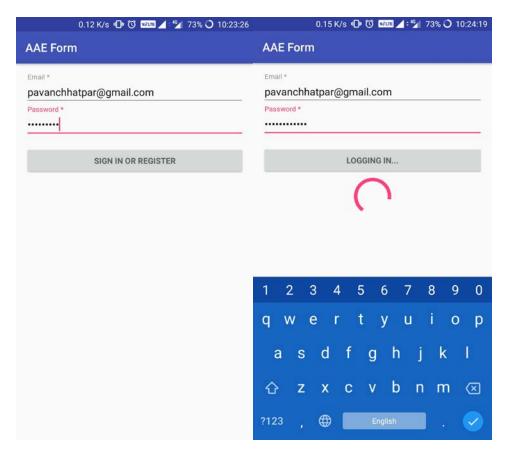


Distribution

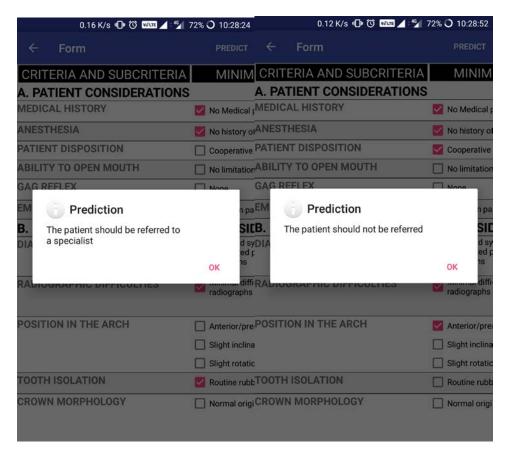
On closer analysis from the perspective of practical usage, just an accuracy figure is not enough. True accuracy lies in misclassifying patients which are to be ideally referred to a specialist as less as possible. In other words, false negatives should be minimum. If a patient not needing a specialist gets referred to a specialist then the scenario is not so bad, the patient will get a better quality treatment. Our algorithm has performed well on these parameters too and the previous graph has been split to give details of the results in the following graph.



GUI Screenshots



0.17 K/	's •D• 🐯 ₩π. 🖊 : 💋 73	3% 🔿 10:24:46	0.06 K/s ⊕	⑦ www ∡: 1/2 73% ○ 10:25:31	0	0.06 K/s 🕩 👸 🚾 🗹 🕍 72% 🔾 10:27:26
← Form		PREDICT	← Form	PREDICT	Form	n PREDICT
CRITERIA AND	SUBCRITERIA	MINIM	AL DIFFICULTY	MODERATE DIFFIC	ULTY	HIGH DIFFICULTY
A. PATIENT COI	NSIDERATIONS					
MEDICAL HISTORY	· [No Medical p	roblem (ASA Class 1*)	One or more medical problems	s (ASA Class	Complex medical history/serious illness/ disability (ASA Classes 3-5*)
ANESTHESIA	[No history of	anesthesia problems	☐ Vasoconstrictor intolerance		Difficulty achieving anesthesia
PATIENT DISPOSIT	ION [Cooperative &	and compliant	Anxious but cooperative		Uncooperative
ABILITY TO OPEN I	HTUOM	No limitation		Slight limitation in opening	h/	Significant limitation in opening
GAG REFLEX	[None		Gags occasionally with radiogramment	apns/	Extreme gag reflex which has compromised past dental care
EMERGENCY COND	OITION [Minimum pa ^{il}	n or swelling	Moderate pain or swelling		Severe pain or swelling
B. DIAGNOSTIC	AND TREATMEN	NT CONSIL)	ERATIONS		e of usual	Confusing and complex signs and
DIAGNOSIS	[Signs and syr recognized ru conditions	nptoms consistent with ulpal and periapical	Extensive differential diagnosi signs and symptoms required	s or usual	symptoms: difficult diagnosis History of chronic oral/facial pain
RADIOGRAPHIC DI	FFICULTIES [Minimal diffi ^c radiographs	ulty obtaining/interpreting	Moderate difficulty obtaining/i radiographs (e.g., high floor of narrow or low palatal vault, pretori)	esence of	Extreme difficulty obtaining/interpreting radiographs (e.g., superimposed anatomical structures)
POSITION IN THE A	ARCH [Anterior/pre	nolar	1st molar		2nd or 3rd molar
		Slight inclina		☐ Moderate inclination (10-30°)		Extreme inclination (>30°)
		Slight rotatic		☐ Moderate rotation (10-30°)	ion required	Extreme rotation (>30°)
TOOTH ISOLATION			er dam placement	Simple pretreatment modification	ion required	Extensive pretreatment modification required for rubber dam isolation
CROWN MORPHOL	OGY (al crown morphology	Full coverage restoration		Restoration does not reflect original anatomy/alignment
01101111111011111102		Normal origi		Porcelain restoration		Significant deviation from normal tooth/ root form (e.g., fusion, dens in dente)
				☐ Bridge abutment	al tooth/	
				Moderate deviation from norm root form (e.g., taurodontism,	microdens)	
				Teeth with extensive coronal d		Extreme curvature (>30°) or S-shaped
CANAL AND ROOT	MORPHOLOGY I	Slight or no	urvature (<10°)	Moderate curvature (10-30°)	from root	curve Mandibular premolar or anterior with 2
OAITAL AITO NOOT	montriozoo1 [<1 mm in diameter)	Crown axis differs moderately axis. Apical opening 1-1.5 mm	in diameter	roots
	·	closed apex		axio. reposit opening 1 1.0 min		Maxillary premolar with 3 roots
						Canal divides in the middle or apical third
						☐ Very long tooth (>25 mm) ☐ Open apex (>1.5 mm in diameter)
RADIOGRAPHIC AI	PPEARANCE [Canal(s) visi	le and not reduced in size	Canal(s) and chamber visible I in size	out reduced	Indistinct canal path
OF CANAL(S)		_		Pulp stones		Canal(s) not visible
RESORPTION	Г	No resorptio	evident	Minimal apical resorption		Extensive apical resorption
						Internal resorption
						External resorption
C. ADDITIONAL CONSIDERATIONS						
TRAUMA HISTORY		Uncomplicat	d crown fracture of mature eeth	Complicated crown fracture of teeth		Complicated crown fracture of immature teeth
		→ or immature		Subluxation		Horizontal root fracture
						Alveolar fracture
						☐ Intrusive, extrusive or lateral luxation
ENDODONITIC TRE	ATMENT HISTORY					Avulsion
LADODON IIC IKE	ATMENT HISTORY [No previous t	reatment	Previous access without comp	lications	Previous access with complications (e.g., perforation, non-negotiated canal, ledge, separated instrument)
DEDIODONTAL THE	OODONTIC	7				Previous surgical or nonsurgical endodontic treatment completed
PERIODONTAL-ENI CONDITION	DODONTIC [None or milq	periodontal disease	Concurrent moderate periodor	ntal disease	Concurrent severe periodontal disease
						Cracked teeth with periodontal complications
						Combined endodontic/periodontic lesion
						Root amputation prior to endodontic treatment



Conclusion

Thus, we have prepared a prediction model to decide whether an endodontic case should be referred to a specialist or not. To make it easily usable by dentists in practice, a user friendly mobile app has also been prepared to make predictions on input data. The predictive model gives accuracy ranging between 89% - 96%.