Inclusion Prediction Model

Configuration Options

To learn about configuration settings, which enable you to toggle Manual updating vs. Automatic and Displayed vs. Hidden, see the Settings page.

How Inclusion Predictions Works

The Inclusion Prediction Model learns from your screening activity on the specific nest you are Screening. It compares the metadata and Abstract content between Included and Excluded records, checks its own accuracy, and then provides a prediction about how likely each Unscreened record is to be Included.

Running the Inclusion Model

In its default setting, the Inclusion Model must be run manually. To do so, click "Train Inclusion Model" on the Screening panel:

Abstract Full Text Supplements Related Reports		₹	Navigation	n ^
Zadeh, 2022				Skip
Stroke in Middle Eastern children with cancer: prevalence and risk factors.				
OBJECTIVE To determine the prevalence and to characterize the different types of strokes in children with cancer at the Children's Can	cer Center of Lebanon (CCCL), in addition to	₹	Screening	
assess the factors and clinical findings leading to stroke in children. METHODS We retrospectively reviewed the medical records and b	rain images (MRIs and CTs) of children admitted	Full Text Review		Train Inclusion Model
to the CCCL and diagnosed with cancer between years 2008 and 2017. Brain images were reviewed for the strokes' onset, size, locatio	n, possible origin, its recurrence and type:	Upload Full Text		<u>1</u>
intracranial hemorrhage (ICH), acute arterial ischemic stroke, and cerebral sinus venous thrombosis (CSVT) with and without venous ir	farct. Medical charts of the patients were	Exclude:		
reviewed for age, sex, their type of cancer, the treatment protocol they followed, and abnormal findings on their laboratory studies an	d neurological exams. RESULTS Out of the 905	Search Reasons		2
charts reviewed, twenty-seven children with variable types of cancer had strokes, with a prevalence of 2.9%. Their median age at cancer diagnosis was 9.4 (4.8-13.7) years and the		Select Reason 🗟		
median age at stroke onset was 10.6 (6.7-15.5) years. The median time between the cancer diagnosis and the stroke episode was 6 mo	nths. CSVT cases were the most common (60%)		Select Reason p	<i>s</i>
followed by acute arterial ischemic (22%) and hemorrhagic strokes (18%), with CSVT being the latest to occur. We observed that the c	lifferent types of <mark>strokes</mark> were related to some			
types of cancer. Of the children that had acute arterial ischemic stroke in this cohort, 83% had brain tumors, of the children who had C	SVT, 87.5% had leukemia, and of the children			
who had hemorrhagic stroke, 40% had leukemia. Neurological abnormalities were more prevalent in acute arterial ischemic stroke (80	%). Patients with CSVT recovered better than			
those with other types of strokes. Strokes recurred in 60% of ischemic strokes. L-Asparaginase was significantly associated with CSV1	i. CONCLUSIONS The prevalence of strokes was			
2.9% in children with cancer. We were able to identify factors related to the types of the stroke that occurred in children including the	type and location of the cancer the type of			
treatment received, and stroke recurrence.				
		Include:		
Population/Problem Intervention Outcome Vour Keywords 🖉 —			Include	
(Keywords) (Bibliographic fields	→) (Edit)	₹	Tagging	\sim
		₹	Comments ((0) 🗸
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Once the modal opens, click "Train New Model." It may take a minute to train, after which it will populate the histogram on the left.

Interpreting the Model

Once the Model is trained, you should see a histogram (red box) where Included, Excluded, and Unscreened records are represented by red, green, and purple curves, respectively:

	Inclusion Rate Modeling				
※ いろう ちんちゃ	Inclusion models predict the likelihood that records will be included in your Nest. Models are trained using the set of previously screened records. As more records are screened, the model should be retrained to achieve improved accuracy.				
E	The histogram below displays modeled inclusion probabilities for records in your Nest. Modeled probabilities are broken out by included, excluded, and unscreened records. Accurate models will have high inclusion probabilities for included records and low inclusion probabilities for excluded records. A hig cross validation AUC (> 0.7) indicates that the model should be expected to generalize well to the remaining unscreened records.	ıh			
E	It is recommended to have at least 5 included records and 20 screened records before training a model. This Nest currently has 377 screened records, of which 19 are included.				
N A L	Included Excluded Unscreened Inclusion model training				
	Excluded Unscreened Inclusion model training Complete!				
n M d C r S	0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 Inclusion Probability (ROC-AUC 0.95)	Close			

Odds of inclusion are presented on the x-axis (ranging from 0 to 1).

What if there is not enough evidence to train the Model?

As noted in the modal, the Inclusion Prediction Model trains only on the decisions you and your team have made in that specific nest, so you must have screened at least 20 studies and included at least 5 to provide a minimum sample to train on.

If there is insufficient evidence to train the model, complete more screening until the "Train New Model" button becomes available.

How Accurate is the Model?

Since the Model is trained on a nest-by-nest basis, its accuracy ranges based on how many records it can train on and how many patterns it can find in inclusion activities.

You can see the accuracy in the modal (see red arrow in the image above). Accuracy is presented as a Receiver Operating Characteristic Area Under the Curve (ROC-AUC).

ROC-AUC has a minimum of 0 and a maximum of 1, where 1 indicates that when the Model checks its predictions on existing inclusion decisions, it had no false positives or negatives. So, high ROC-AUC (0.85-0.99) indicates that trusting the Model may be warranted, while lower ROC-AUC means that more screening may be necessary to train it further, or the patterns in inclusion decisions are too disparate for accurate prediction.

Implications for Screening

Once trained, the Inclusion Prediction Model will automatically re-order studies in Screening so that the most likely to be included are presented first. This assists in identifying relevant studies early.

Inclusion Prediction is also available as a filter in Inspector, which can assist with finding records

based on their chance of inclusion. Bulk Actions can also be taken at your discretion, but ensure that you are careful in excluding studies if you have not reviewed their Abstracts at least!

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