

ABDUCTIVE LEARNING: BRIDGING MACHINE LEARNING AND LOGICAL REASONING



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CONTENT

- Problem Statement
- Motivation
- Dataset
- Methodology.
- Architecture
- Inputs & Outputs
- Results

PROBLEM STATEMENT

- Integration of Perception and Logical Reasoning
- Challenge of bridging the gap between sub-symbolic perception and symbolic reasoning

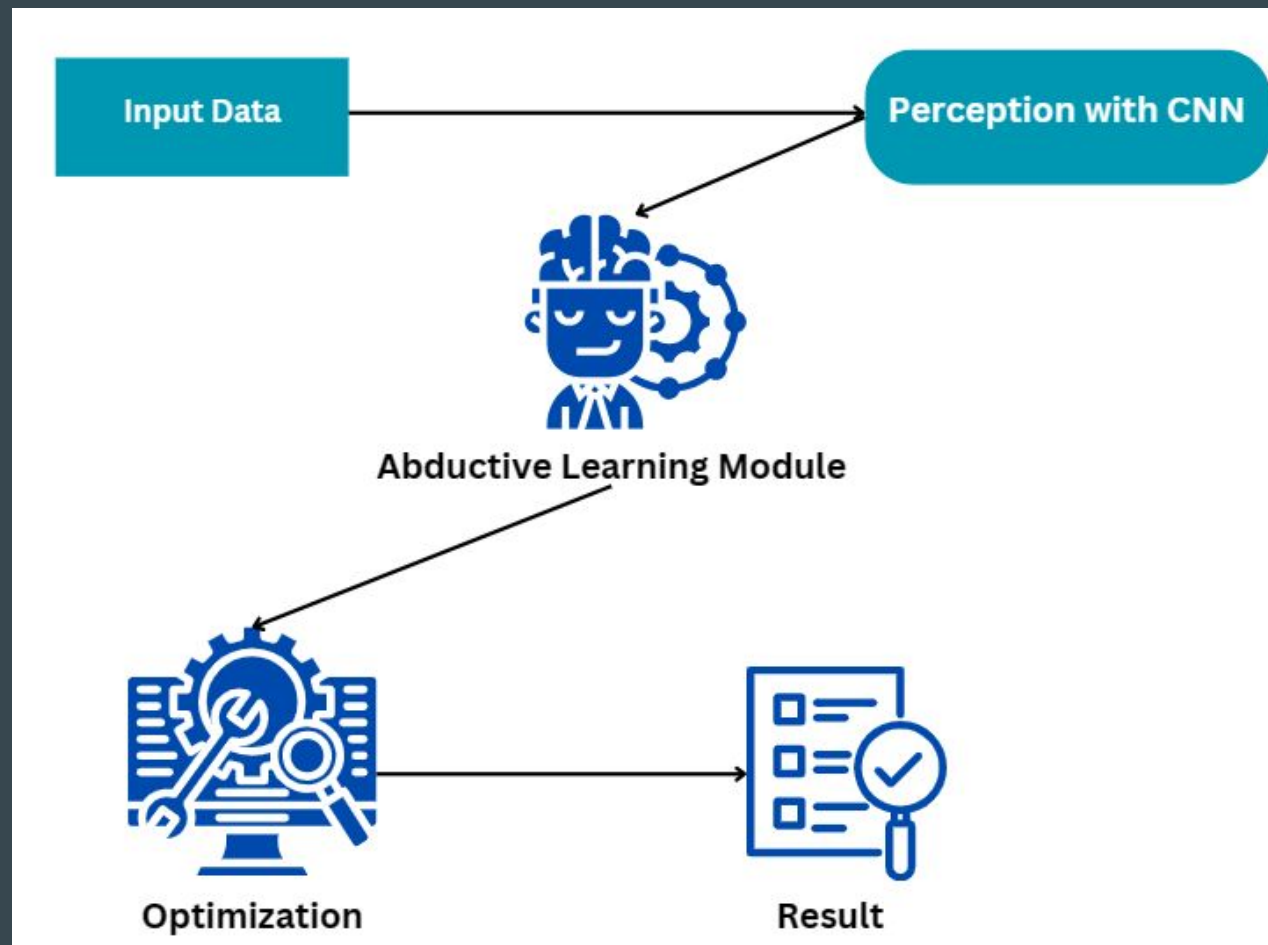
MOTIVATION

- Creating a framework ML can perceive primitive logic from facts
- Developing a ML model to use symbolic reasoning based on domain knowledge base.

DATASET

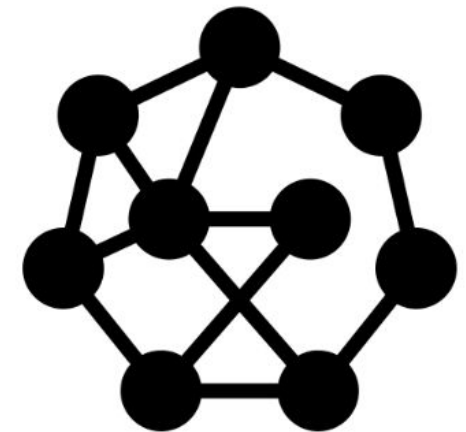
- MNIST dataset: The MNIST dataset is used to train models for recognising handwritten digits. (example: 1, 0, + and =)

Methodology



CNN

- The CNN is used for classifying the symbols in the dataset i.e.
- It learns the mapping $p: X \rightarrow P$, which in this case, is a mapping from images to labels in the set $\{0,1,+,=\}$.
- The CNN will initially be trained on random labels, which need to be fixed iteratively.



CNN

Abductive Learning

- We know the structure of the equation, that is, the digit is a sequence of “0”s and “1”s, and each equation has structure $X+Y=Z$.
- '+' is known to be a bit-wise operation, and as the digits are binary, '+' could represent any one of the 16 binary operators.
- X, Y and Z have constant length.



Abductive Learning Module

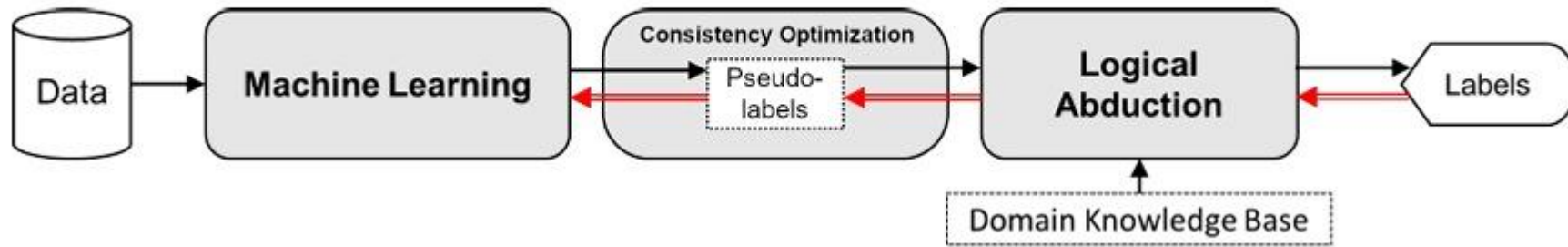
Optimization

- ABL tries to maximise the consistency between the abducted hypotheses H with training data D , given background knowledge B . It can be defined as:
 - $\text{Con}(H \cup D; B) = \max |D_c|$, where $D_c \subseteq D$
- Uses greedy optimization



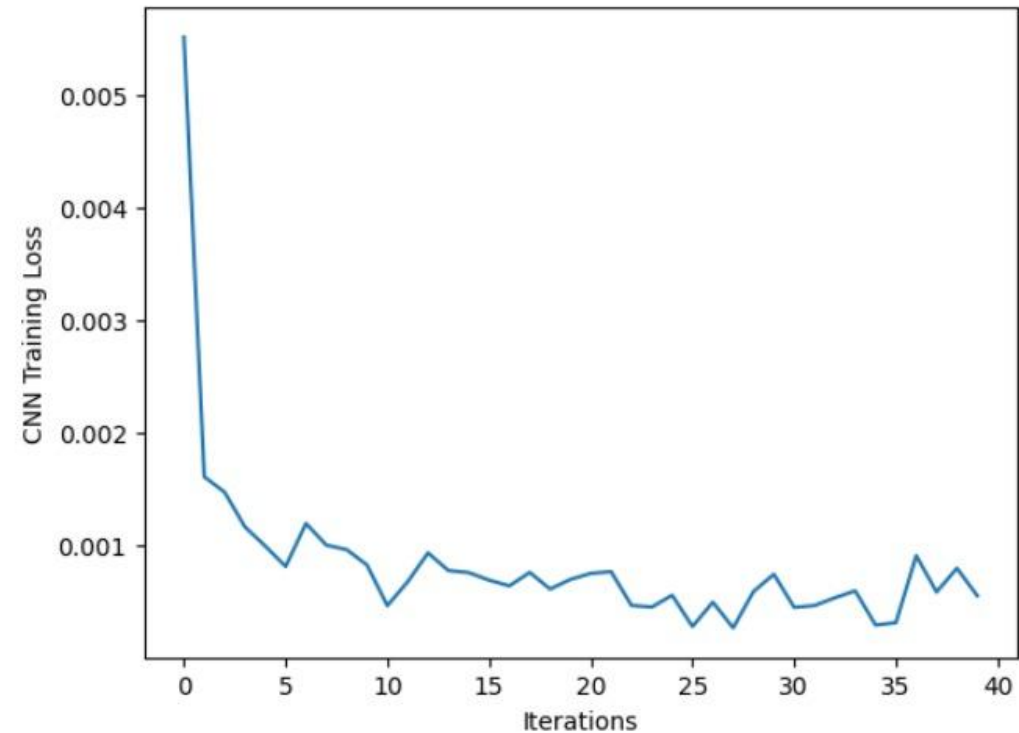
Optimization

ARCHITECTURE



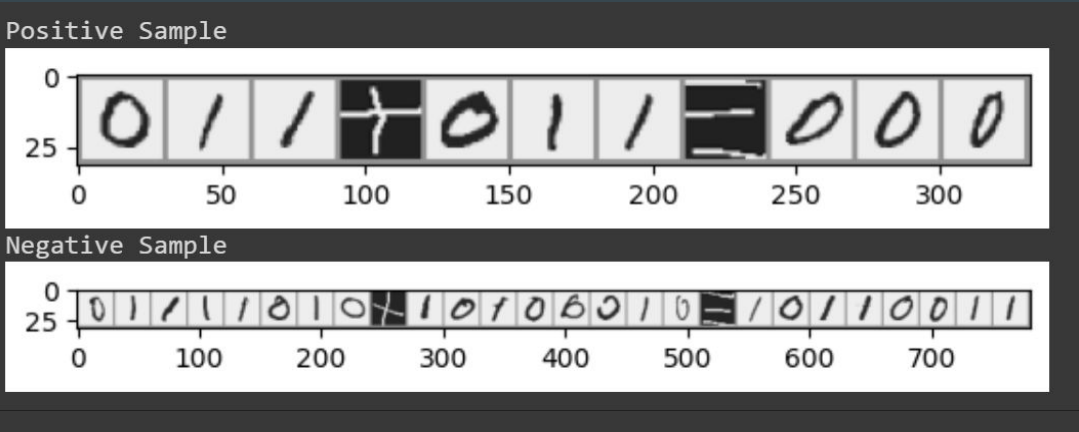
EXPECTED RESULTS

- Initially, learning is rapid and loss rapidly decreases.
- The loss curve fluctuates, notably in the early iterations.
- The loss stabilizes at 0.001-0.002 as the model converges to a stable state.
- No indications of overfitting as loss doesn't significantly increase.
- Indicates that the model is acquiring knowledge efficiently and adapting to training data.



RESULTS

Model training and evaluation with MINST

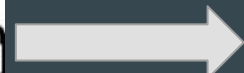


Consistency score if 'model' is used for perception, given a set of equations and the corresponding labels


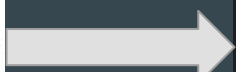
Precision	0.994819
Recall	0.898785
Accuracy	0.940909
F1-score	0.944367

RESULTS

Handwritten math equation recognition using Conv2D from keras and solution

A white rectangular box containing the handwritten text "8 + 5". The numbers and the plus sign are drawn in a simple, slightly irregular black ink style.A thick, light gray arrow pointing from the equation box to the result box.

Symbols: [8, 5]
Operations: ['+']
[{'Z': 13}]

A white rectangular box containing the handwritten text "2 * 3". The numbers and the asterisk are drawn in a simple, slightly irregular black ink style.A thick, light gray arrow pointing from the equation box to the result box.

Symbols: [2, 3]
Operations: ['*']
[{'Z': 6}]

Conclusion

- Implemented the paper
- Bridging the gap between sub-symbolic perception and symbolic reasoning is possible

What we learned from the project?

- Simultaneous enhancement of both perception (comprehending the input data) and reasoning (applying logic/knowledge)
- How machines can perceive primitive facts from learning

REFERENCES

- "Bridging Machine Learning and Logical Reasoning by Abductive Learning" by Wang-Zhou Dai, Qiuling Xu, Yang Yu, Zhi-Hua Zhou.