An Inception Architecture-Based Model for Improving Code Readability Classification

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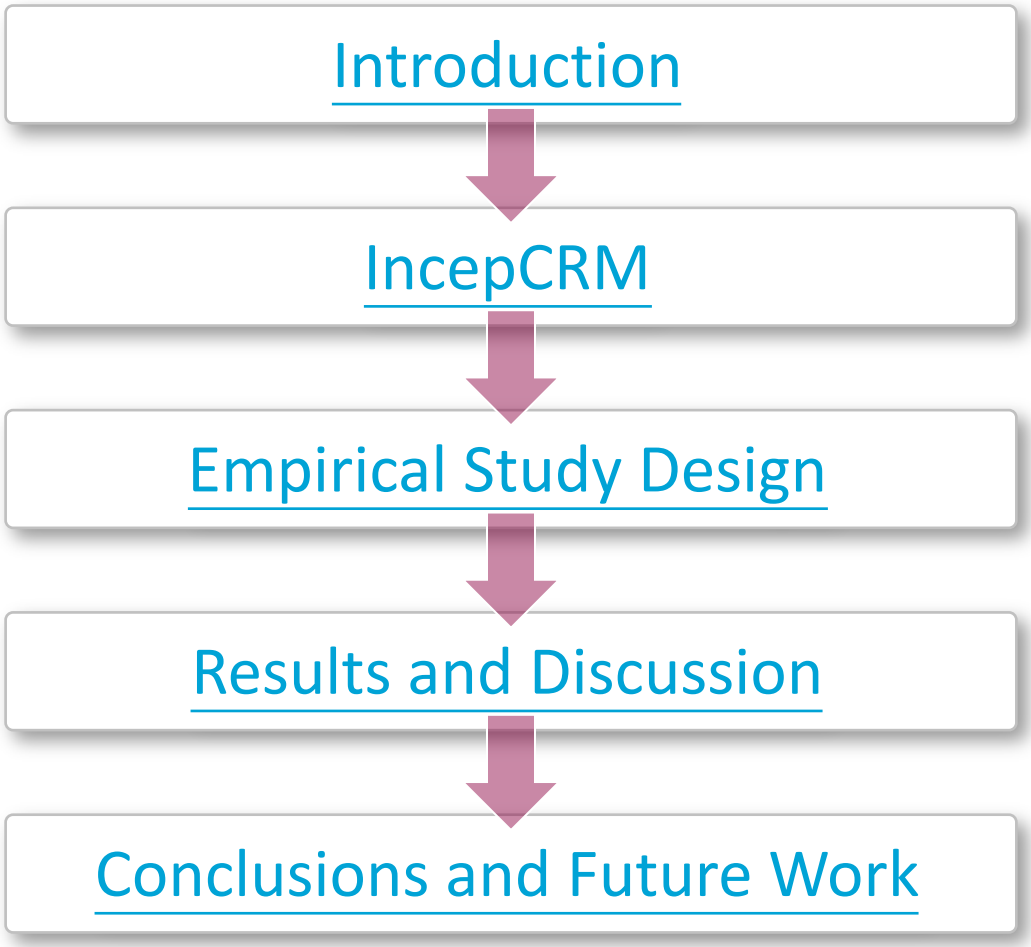
Presentation Outline



Background

- Code Readability can be defined as a human judgment of how easily a piece of code can be read and understood.
- As shown in Figure 1, it is desirable to have readable code that is less erroneous, more reusable, and easier to maintain.

```java
/**
 * Add one zero if necessary
 * @param number
 * @return
 */
private CharSequence addZero(int number) {
  StringBuilder builder = new StringBuilder();

  if (number < 10) {
    builder.append('0');
  }

  builder.append(Integer.toString(number));
```

Readable Code (Mean Readability Score - 4.02)

```java
  /**
   * Creates a new <code>DisbandUnitAction</code>.
   *
   * @param freeColClient The main controller object for the client.
   */
  DisbandUnitAction(FreeColClient freeColClient) {
      super(freeColClient, "unit.state.8", null, KeyStroke...
      putValue(BUTTON_IMAGE, freeColClient.getImageLibrary()...
      ImageLibrary.UNIT_BUTTON_DISBAND,
              0));
      putValue(BUTTON_ROLLOVER_IMAGE, freeColClient...
      getUnitButtonImageIcon(
              ImageLibrary.UNIT_BUTTON_DISBAND, 1));
```

Unreadable Code (Mean Readability Score - 2.01)

Figure 1: Readable Code vs. Unreadable Code

Introduction

❖ Traditional Models

Collect labeled data by conducting a large-scale survey, inviting multiple human annotators to rate code snippets by readability.

Handcraft features from different aspects that intuitively seem to have some effect on code readability.

Train a machine learning classifier using data collected from the first phase.

VS

❖ IncepCRM

Eliminate the need for manual feature engineering.

Apply the information of human annotators as the auxiliary input for model training.

Propose a modified Inception module that can automatically learn multi-scale features from the source code.

Convolutional Neural Network

- Feature Learning Network
  - Alternating convolutional and pooling layers
- Classification Network
  - One or more fully-connected layers

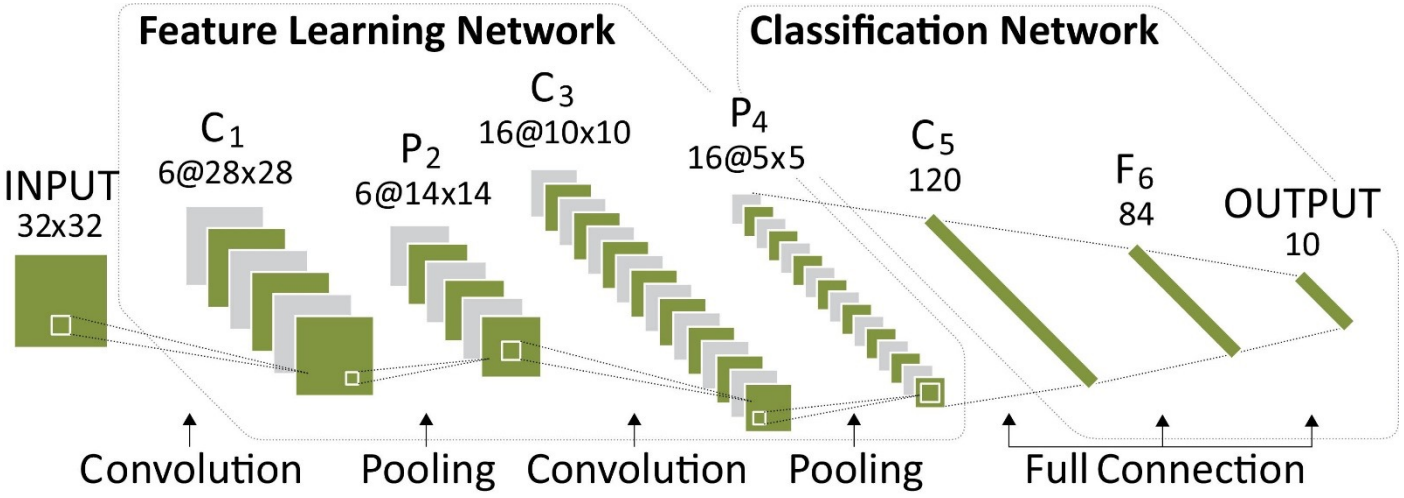


Figure 2: Architecture of LeNet-5 (A Classical Convolutional Neural Network)

Proposed Approach

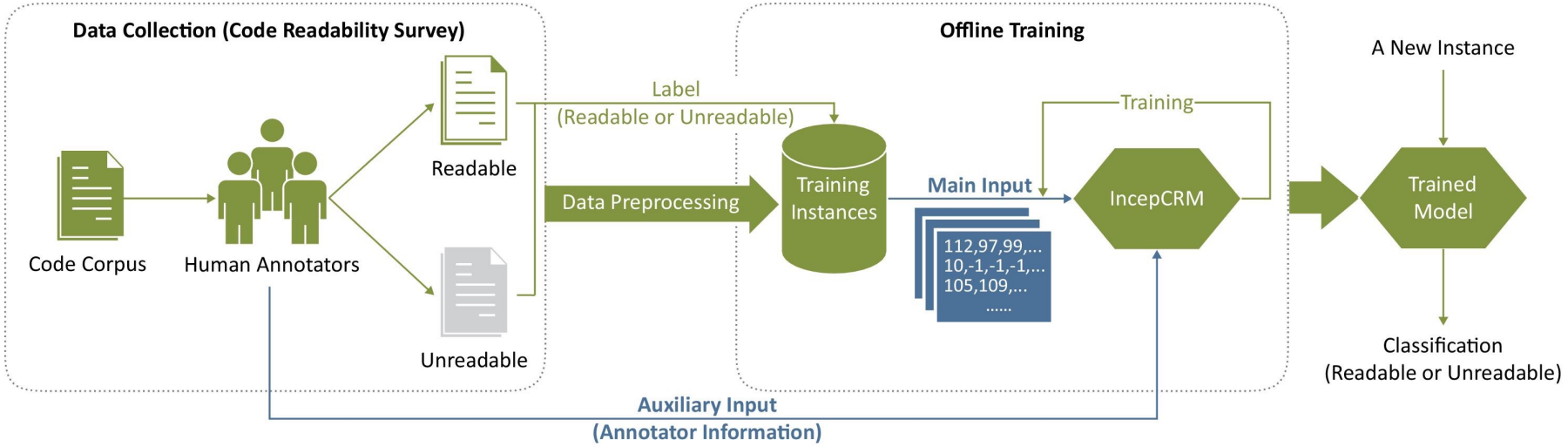
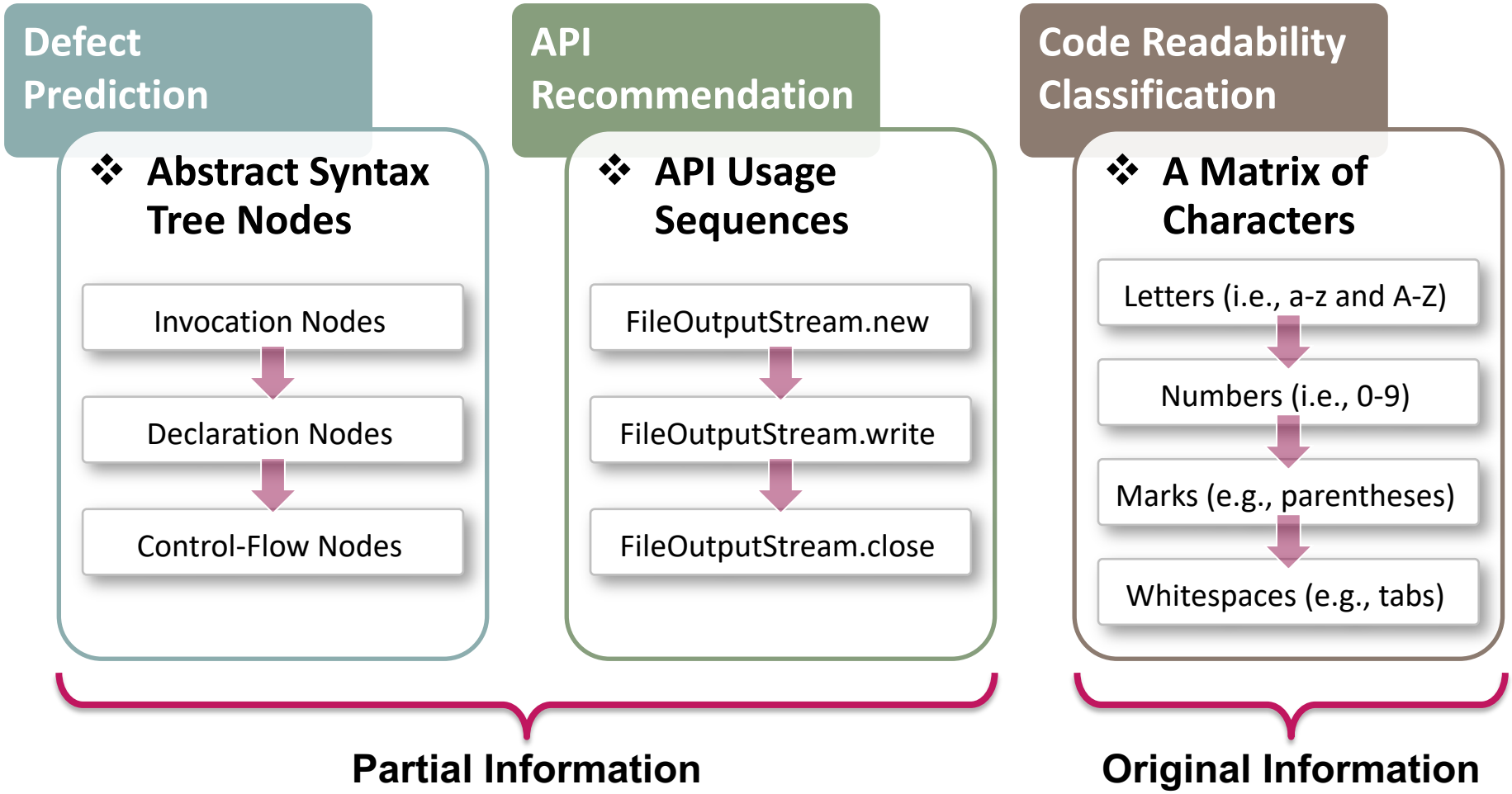


Figure 3: Approach Overview

Data Preprocessing



Annotator Information

- The number of annotators who have rated a code snippet
  - Code snippets that have been rated by more annotators are more reliable than those with less.
- The standard deviation of readability scores on a code snippet
  - A lower standard deviation indicates greater consistency among annotators.

Model Architecture

- Inspired by GoogLeNet, we adapt the Inception architecture for code readability classification.

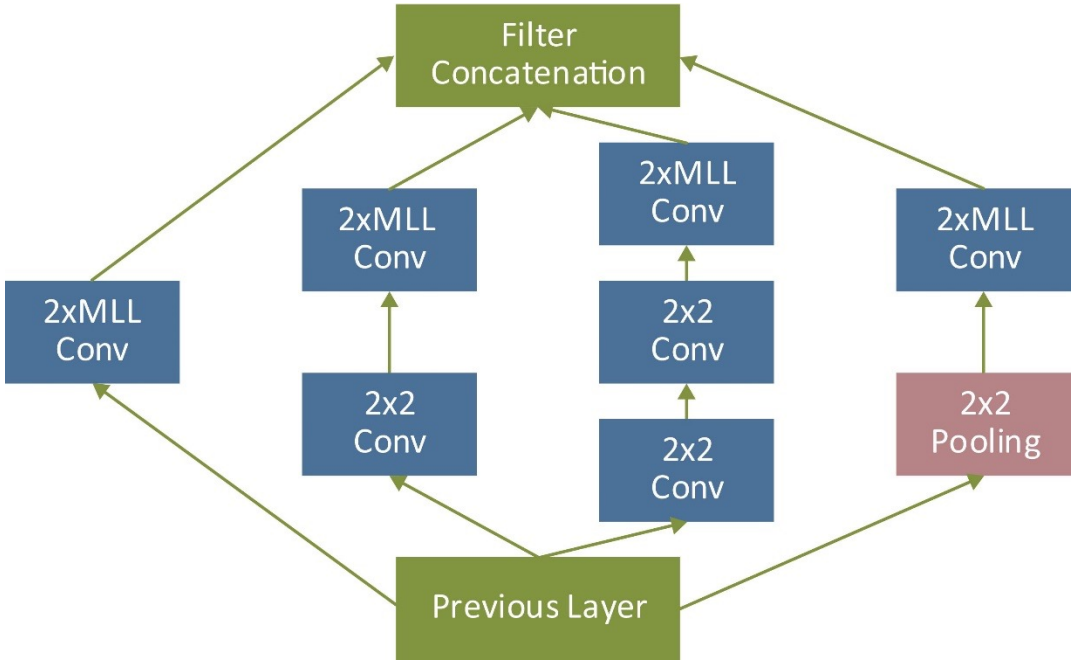


Figure 4: The Inception Module used in IncepCRM

- For computational savings, we apply the same receptive field in each module.
- The width of the filter size on top levels is set as the maximum line length (MLL).

Model Training

- We use the Keras library with Tensorflow backend to implement IncepCRM.
- The cross-entropy loss is adopted to calculate the error rate between actual and desired outputs.
  - N=32 is the number of data samples (the batch size)
  - M=2 is the number of classes (Readable and Unreadable)

$$J = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} p_j^{(i)} \log q_j^{(i)}$$

- We train the model in a supervised manner using the Adam optimizer with a learning rate of 0.001.

Empirical Study Design

- RQ1: Does annotator information contribute to the performance of IncepCRM?
- RQ2: To what extent does IncepCRM outperform the existing models in code readability classification?

Data Preparation

- A corpus of labeled code snippets as the ground-truth
- A Likert scale ranging from 1 (very unreadable) to 5 (very readable)
  - the Readable group VS the Unreadable group

Table 1: Statistical Summary of the Code Corpus

Dataset	Source	Total # of Code Snippets	Total # of Annotators	Lines of Code	
				Mean	SD
D_{Buse}	SourceForge	100	121	7.61	2.59
D_{Dorn}	SourceForge	360	5000+	29.74	16.36
$D_{Scalabrino}$	SourceForge	200	9	26.56	10.29

Measures for Evaluation

- Accuracy shows the ratio of all correctly classified instances.

$$Accuracy = \frac{tp + tn}{tp + fp + tn + fn}$$

- The higher the metric value, the better the model performance.

Analysis Method

- To answer RQ1, we examine whether there exists significant difference between the performance of IncepCRM with and without annotator information using robust test statistics.
  - The Brunner-Munzel test (significance level $\alpha=0.05$)
  - Cliff's delta

Analysis Method

- To answer RQ2, we compare IncepCRM with five state-of-the-art code readability models.
  - Buse et al.'s Model (M_{Buse})
  - Posnett et al.'s Model ($M_{Posnett}$)
  - Dorn et al.'s Model (M_{Dorn})
  - Scalabrino et al.'s Model ($M_{Scalabrino}$)
  - A Comprehensive Model (M_{All})
- To enable a fair comparison, we apply different machine learning techniques as the underlying classifier for each model.
  - Logistic Regression (LR), Bayesian Network (BN), Multilayer Perception (MLP), Sequential Minimal Optimization (SMO), and Random Forest (RF).

Results and Discussion

- RQ1 is to investigate whether the addition of annotator information can further improve the accuracy of code readability classification.
  - Negligible for |d-value| < 0.147, Small for |d-value| < 0.330, Medium for |d-value| < 0.474, and Large for otherwise.
- We observe that without annotator information, IncepCRM is able to correctly classify 80.19% of code snippets in our corpus. When annotator information is included, the accuracy increases to 82.76%.
  - The p-value for the Brunner-Munzel test is 0.016 (<0.05) and the d-value for Cliff's delta is 0.641 (>0.474), implying a significant difference with a large effect size.

Table 2: Accuracy Achieved by Code Readability Models

Model		D_{Buse}	D_{Dorn}	$D_{Scalabrino}$
M_{Buse}	LR	0.810	0.786	0.705
	BN	0.760	0.750	0.625
	MLP	0.760	0.742	0.665
	SMO	0.820	0.797	0.670
	RF	0.800	0.781	0.680
$M_{Posnett}$	LR	0.780	0.728	0.660
	BN	0.760	0.681	0.695
	MLP	0.770	0.703	0.655
	SMO	0.770	0.711	0.680
	RF	0.770	0.703	0.605
M_{Dorn}	LR	0.800	0.800	0.755
	BN	0.670	0.747	0.640
	MLP	0.720	0.725	0.685
	SMO	0.770	0.767	0.725
	RF	0.750	0.744	0.690
$M_{Scalabrino}$	LR	0.740	0.772	0.680
	BN	0.530	0.681	0.640
	MLP	0.770	0.742	0.665
	SMO	0.720	0.717	0.650
	RF	0.720	0.742	0.655
M_{All}	LR	0.790	0.839	0.795
	BN	0.720	0.761	0.710
	MLP	0.730	0.778	0.700
	SMO	0.810	0.806	0.770
	RF	0.770	0.789	0.690
IncepCRM		**0.825**	**0.842**	**0.822**

- IncepCRM yields higher accuracy against its competitors across all datasets.

Threats to Validity

- Internal Validity
  - Only a few labeled data are available in the literature, which may not be adequate to train IncepCRM.
  - If the data is prone to errors (e.g., wrong records), then it will be reflected in our results.
- External Validity
  - All projects investigated in this study are collected from SourceForge. It is unclear whether the same findings would be observed in other projects.
- Construct Validity
  - We mainly use accuracy to evaluate the effectiveness of IncepCRM. However, other performance measures such as F-Measure and AUC can also be considered.

Conclusions and Future Work

- We proposed IncepCRM, a novel approach to improve the accuracy of code readability classification based on the Inception architecture.
  - A modified Inception module suitable for code readability classification. (80.19%)
  - The use of annotator information as the auxiliary input for model training. (82.76%)

Conclusions and Future Work

- We conducted a series of experiments on three publicly available datasets.
  - (RQ1) Annotator information is beneficial for classification performance.
  - (RQ2) IncepCRM achieves state-of-the-art accuracy in comparison to previous code readability models.

Conclusions and Future Work

- Improve the performance of IncepCRM
  - Fine-tune hyperparameters (e.g., filter size and dropout rate)
  - Combine multiple deep learning models
  - Experiment with different configurations (e.g., loss functions)
- Find out what exact factors make a code more or less readable

Thank you for your attention!

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