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A Machine Learning-based Knee Osteoarthritis Prognostic Model for Imaging-free Screening at Community

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PURPOSE & BACKGROUND

Background

1. Knee osteoarthritis is a **multifactorial** disease that threatens healthy ageing with **no cure**.

2. **Delayed diagnoses** may cause **irreversible damage** to the knee joint.

3. Current prognoses require **doctor's subjective expertise** coupled with **medical images (e.g X-ray, MRI)** for analysis, which increases direct health costs.

Problem

An **economical** and **accurate** knee osteoarthritis **prognostic model** at **primary healthcare** for **early diagnoses is lacking**.

Purpose

To develop a knee osteoarthritis prognostic model with **data driven approach from machine learning** at **primary healthcare setting** to enable **early diagnoses** without the need for medical images to **reduce direct and indirect health costs**.

Table 1. Risk factors (or features) employed in this study

Feature Group		Feature Name
Non-imaging Features	Demographics	Sex
		Age
		Weight
		Height
		BMI
	Living Habits	Occupational Activity Level
		Smoking Habit
		Alcohol Intake Habit
	Systemic Conditions	Stroke History
		Diabetes History
		Heart Attack History
		Systolic Blood Pressure
		Diastolic Blood Pressure
	Lower Limb Conditions	Knee Injury History
		Knee Surgery History
		Knee Hyperextension or Flexion Contracture
		Crepitus
		Patella Tap Test
		Knee Flexion Pain
		Knee Alignment
		Bulge Sign Test
	Co-existing OA	Hand OA
		Hip OA
		Hand OA
Imaging (X-ray) Features		KL-Grade
		OARSI Osteophyte Grade
		OARSI Joint Space Narrowing Grade
		Minimum Joint Space Width

METHOD

Study Design

Dataset

National Institute of Health Osteoarthritis Biomarkers Consortium (**2,200 knees** studied)

End point of prediction

48-month after the first clinical visit

Knee osteoarthritis progression definition

1) Reduction in **minimum knee joint space** width by more than **0.7mm**; and
2) Increase in the **Western Ontario and McMaster Universities Arthritis Index pain score** by at least **1.8 points** before the end point

Machine Learning algorithm

Self-paced Ensemble (SPEnsemble) for imbalanced classification with 80% and 20% of samples allocated for training and testing respectively.

Performance metric

Average area under receiver operating characteristic curve (AUC) by bootstrapped sampling on the independent test set.

Experiment	Description
Experiment 1	**Compare** the KOA progression **prediction performance** of **Model 1** (Imaging Features + All Non-imaging Risk Factors) and **Model 2** (All Non-imaging Risk Factors only).
Experiment 2	**Compare** the **prediction performance** of different combinations of non-imaging feature groups and select the **most optimal** one, followed by dissecting the model's **relative feature importance** by Shapley Additive Explanations (SHAP) algorithm.

Table 2. Combination of feature groups in model 1 and 2

Model	Feature Group Combination
1	Imaging features, Co-existing OA, Lower Limb Conditions, Systemic Conditions, Living Habits, Demographics
2	Co-existing OA, Lower Limb Conditions, Systemic Conditions, Living Habits, Demographics

RESULT

Result 1

Model 1 had a higher performance of 0.7045 (±0.0358 standard deviation) AUC score, with *Model 2* achieving a lower yet comparable average AUC score of 0.6833 (±0.0330 standard deviation).

Using ***Non-imaging Feature Groups (Model 2) can yield comparable prognostic performance*** with the addition of Radiographic Imaging Features (Model 1).

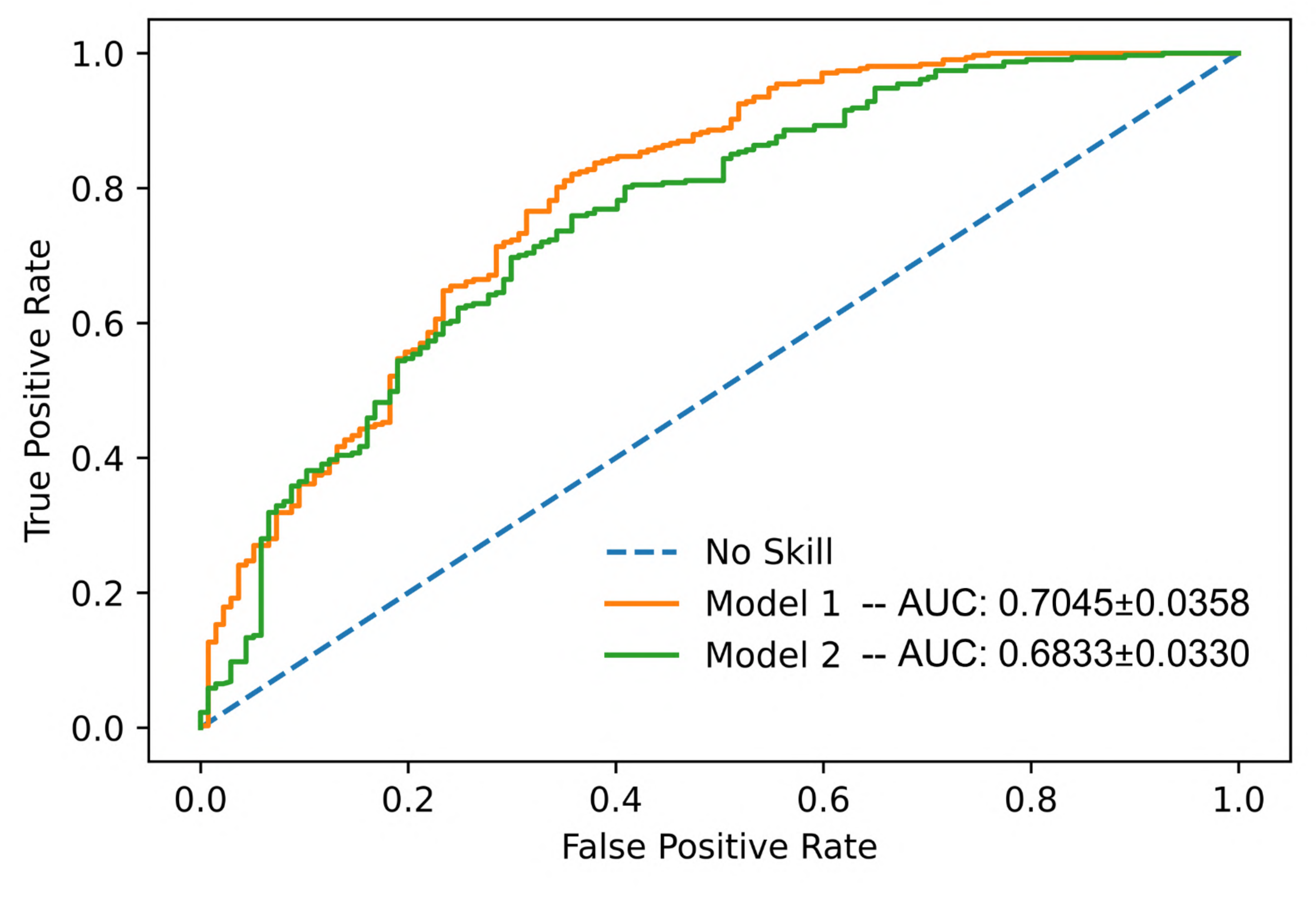

Figure 1. ROC curves of model 1 and 2. Sample standard deviation is employed to depict the error of the AUC metric

Table 3. Combination of feature groups in model 2-6

Model	Best Performing Feature Group Combination	No. of Feature Groups
2	Co-existing OA, Lower Limb Conditions, Systemic Conditions, Living Habits, Demographics	5
3	Co-existing OA, Lower Limb Conditions, Living Habits, Demographics	4
4	Lower Limb Conditions, Systemic Conditions, Demographics	3
5	Co-existing OA, Systemic Conditions	2
6	Lower Limb Conditions	1

RESULT

Result 2

Model 4 with 3 non-imaging feature groups performs the **second best** with **0.6802** (±0.0273 standard deviation) AUC score.

Despite having fewer features, it still performs very similarly as Model 2. Balancing between the number of risk factors and prediction performance, **Model 4 is the most optimal.**

Result 3

Feature importance was revealed from Model 4 (the most optimal model) with SHAP algorithm.

The **lower limb conditions**, such as knee hyperextension, bulge sign, etc, and **systemic risk factors** like BMI, systolic blood pressure play important role in the prediction of KOA.

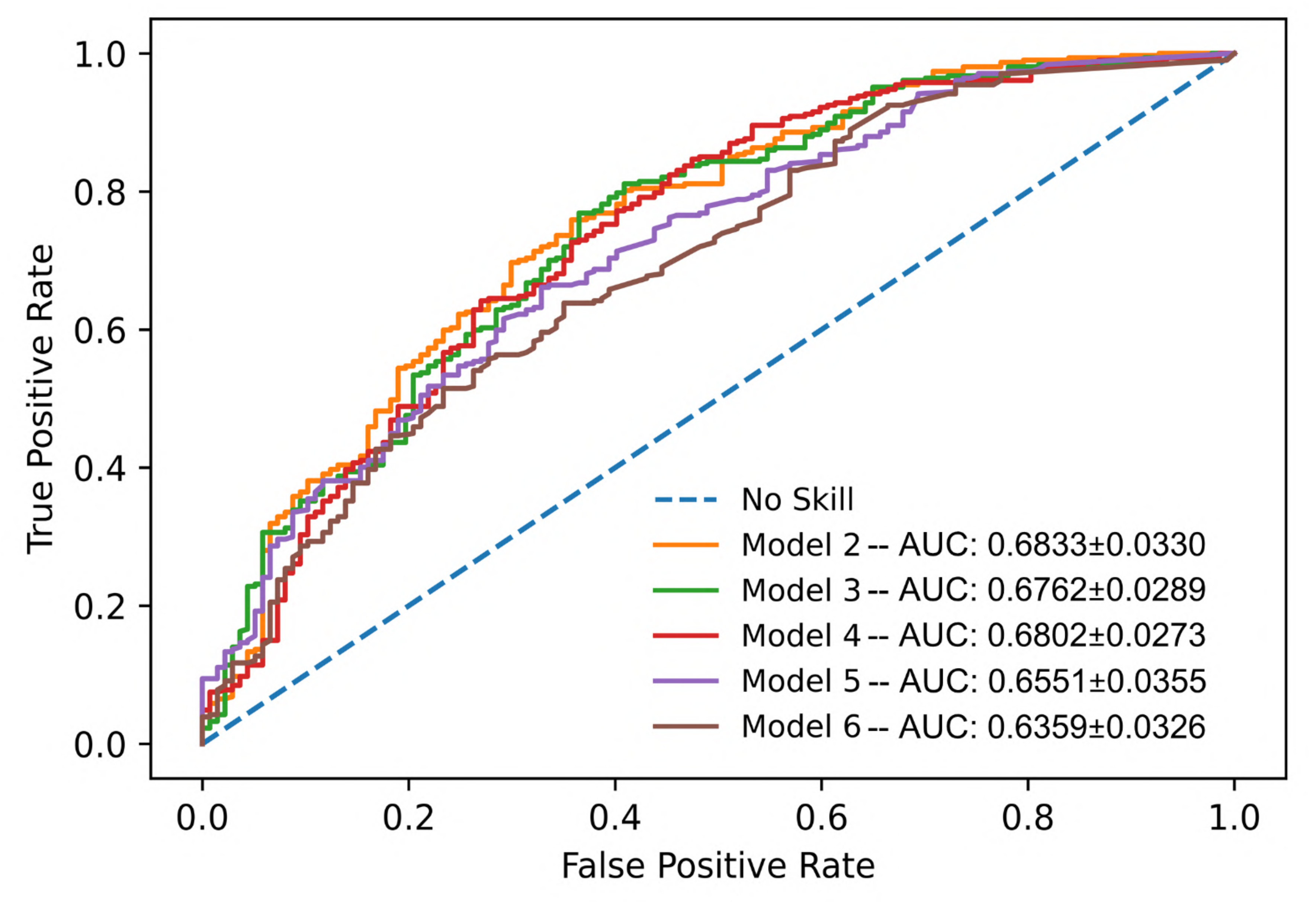

Figure 2. ROC curves of Model 2-6 (different combinations of non-imaging feature groups). Sample standard deviation is employed to depict the error of the AUC metric

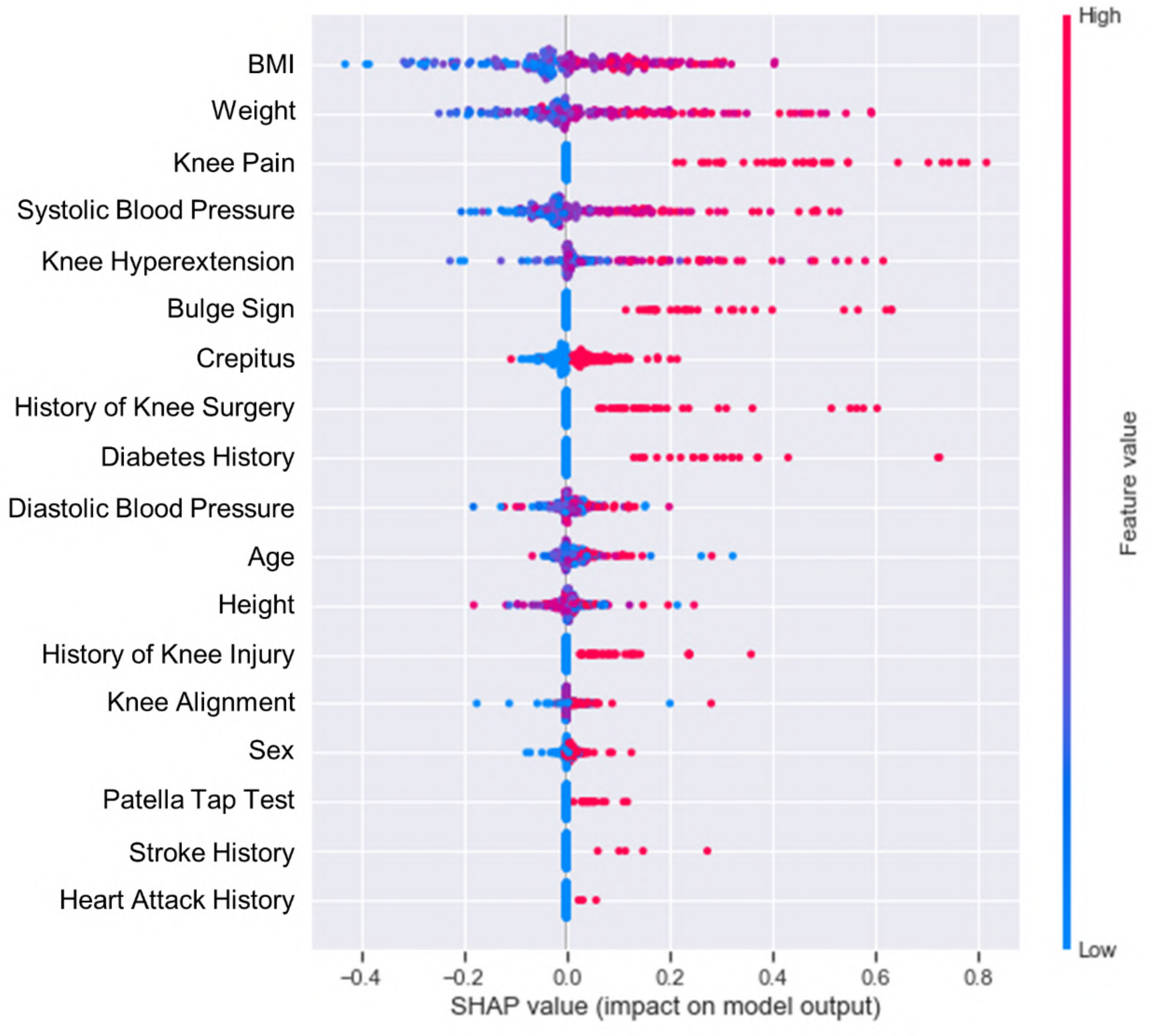

Figure 3. SHAP feature importance plot of Model 4.

CONCLUSION

This study has introduced a **knee osteoarthritis prognostic model** that is based purely on non-imaging risk factors with comparable performance to its counterpart with gold standard medical imaging markers.

Our model could potentially provide an alternative with reduced direct and indirect health cost and may hence **incentivise early disease screening at community and primary healthcare sectors** to facilitate **healthy ageing** and **holistic wellbeing**.