Digital Twin-based Prediction for CNC Machines Inspection using Blockchain for Industry 4.0

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***Abstract*—The rapid growth and advancement of technology in industries provide a better quality of services to the end-user in the industrial Internet of Things (IIoT). The digital twin (DT) is an innovative technology recently developed in Industry 4.0 to provide a virtual representation of physical components, products, or equipment such as computer numerical control (CNC) machines. It can be used to run simulations before manufacturing. However, traditional DT platforms lack data privacy, traceability, immutability, authentication of stakeholders. Moreover, manual prediction of the wearing of the tool condition of the CNC machine is challenging. Motivated from these gaps, in this paper, we propose a six-layered architecture for DT of CNC, which predicts CNC tool wear detection using a novel ensemble technique based soft voted prediction model consisting of XGBoost, random forest, and AdaBoost models. The proposed architecture also incorporates the public Ethereum blockchain (BC) to maintain the aforementioned issues of authentication, traceability, and transparency through constraints and automation programmed into the smart contracts (SC) developed. We evaluate the proposed scheme's performance through simulation and compare it with other traditional approaches concerning several performance parameters (accuracy, F1-score, precision, and recall). The result shows that the proposed approach outperforms the traditional approaches on these same performance parameters such as accuracy, F1-score, precision, and recall.**

Index Terms*—Digital Twin, Artificial Intelligence, Ensemble Learning, Blockchain, Smart Contract, CNC, Industry 4.0

I. Introduction

The term Internet of Things (IoT) was first presented in 1999 by Mr Kevin Ashton. Since then, with advancements in wireless technologies, IoT has benefited many sectors in areas such as smart homes, transportation, healthcare, etc. IoT is believed to bring a significant change in the industrial sector, too, prompting the idea of IIoT. The first three industrial revolutions relied on mass labour, water and steam power, electrical energy, and automated production [1]. The ongoing fourth revolution (Industry 4.0) will rely on *Cyber-Physical Systems* (CPS) [2]. The term IIoT can be explained as the network of smart and connected components used in industries deployed to get a high production rate along with a reduction in operational charges through live supervision, efficient management, and control of industrial assets, processes, and operational time [3]. A recent study regarding the scope of IIoT suggests that while we reach 2025, there will be around 70 billion internet-connected Things, and these devices can produce about 180 trillion gigabytes of data every year. Moreover, the IIoT market share is predicted to be around 14.2 trillion US dollars by 2025.

As the industrial machines are being instrumented with sensors and actuators to collect the digital data and monitor the activities, to further ease the functioning, DT's new technology steps in. DT was first coined in 2002, by-product lifecycle management space to create a complex manufacturing system of spacecraft [4]. National aeronautics and space administration (NASA) revisited DT concept in the year 2012 and coined it as a multi-scale, multi-physics, probabilistic, ultra fidelity simulation that reflects, promptly, the state of a corresponding twin based on the historical data, real-time sensor data, and physical model [5]. DT is a digital replica of a system, process, device, product which takes the data from the physical world and incorporates it to create simulations and predictions, thus creating CPS.

With the help of modern microchips, sensors, and information technologies, it is possible to create smart products that can gather data about their environmental condition, state, loads, which can be further sent to the virtual product model. This huge data generated can be fed into the DT before the pre-production phase and the production phase. This will consider the alteration of machine settings for the work-in-process (WIP) in line dependent on reproductions in the virtual world before the physical changeover, reducing machine arrangement times and increasing quality. Presently, DT technology is being turned out by Chevron for its oil fields and refineries and hopes to spare a large number of dollars in maintenance costs. As a major aspect of its pitch, Siemens says that using DTs to model items that have not been made currently can diminish item defects and abbreviate time to market. Nonetheless, DT involves a portrayal of the gadgets, 3D rendering, and details of all sensors in the gadget. It is continuously fed sensor readings that simulate real-life options. But DT itself is not capable of future state identification and predict the product behaviour. Hence, artificial intelligence (AI) can be embedded with DT for such applications.

The role of AI is crucial for DT's better performance, which can help engineers evaluate many design alternatives and thus enhance the overall design process. These engineers can uncover the design issues, which were not considered during the DT designing by running AI solutions [6]. AI can reduce running simulations, which other design software takes about a day or two to run [7]. AI can be trained on the data generated by running the simulations. Adding machine learning (ML) to these systems can help predict real-world data, which otherwise needs a lot of testing. ML can make the DT more intelligent in learning from past information and to make changes in its operation accordingly.

However, the application of AI algorithms for prediction is still prone to data attacks. In an industrial zone, there are several employees involved that use CNC machines during production. These employees can manipulate the data stream that serves as an input to the DTs. Hence, it is necessary to have some authorization involved for the system stakeholders. Moreover, for the problem of backtracking, some traceability must be involved. Therefore, BC technology can provide a solution to the problems mentioned above [8].

Many researchers have contributed to this domain. For example, the authors in [9] demonstrated the technique for modelling DT for the CNC machine tool (CNCMT), which includes a mapping technique, multi-domain suitable modelling technique, and an autonomous strategy. Zehnder *et al.* used semantic labelling to represent industrial data in the DT [10]. Streams are commented on using the idea of semantic labels, which permits assigning qualities, for example, area or kind of the underlying advantages for data streams. The author's commitment comprises of asemantic schema portrayal that arranges comparative data streams, allowing subscribers to devour comparable data from numerous assets within a single data analytics pipeline. Also, Schroeder *et al.* to model attributes related to DT proposed AutomationML and shown that the model is useful for data exchange among various DT connected systems [11]. The authors in [12] proposed the procedure to support the interactive design of optimal NC machining programs of DT construction for a sheet metal punching machine. Then, Tao *et al.* in [13] put forward the DT workshop concept, which comprises the DT operating mechanism, workshop system composition, and implementation method.

A. Motivation

Although the appreciable research is carried out in DT and its applications, the research work is much from a theoretical perspective. Also, the authors have not explored much about simulated BC for DT in IIoT to ensure data integrity, transparency, and traceability of activities done within the system during modelling of CNC and its prediction. Hence, we, the authors, are motivated for this research work. In this paper, the proposed architecture for DT of CNC machines fulfils the need for security, data traceability for DT using BC [14]. This architecture also uses a novel ensemble learning-based prediction model for predicting tool wearing of CNC through DT.

B. Research contributions

The research contributions of this paper can be summarized as follows.

- A hybrid six-layered architecture using AI and BC is proposed for DT of CNC machines to simulate and solve the tool wearing these machines used in industries.
- Then, a novel ensemble learning-based soft voting classification algorithm consisting of XGBoost, Random Forest, and AdaBoost is proposed, which predicts the CNC tool wear conditions.
- Finally, BC and prediction models are simulated, and performance evaluation of the proposed scheme is done by considering accuracy, f1-score, precision, and recall.

C. Paper organization

The flow of the paper from here is organized as follows. Section II discusses the proposed architecture and give details about each layer. Section III discusses the performance evaluation of the novel ensemble soft voting classifier, and finally, Section IV concludes the paper.

II. Proposed approach

In the current section, we propose a six-layered architecture for DT for CNC machine as shown in Fig. 1.

A. Physical Layer

The physical layer is associated with the factory line, where complex manufacturing machines such as CNC and data collectors are arranged. These CNC machines include various types of equipment, such as cutting tools, spindles, actuators, workpieces, etc. These devices are interconnected to produce a single complex machine that encompasses all and performs a complicated task. Various sensors are arranged within these machines to collect all the required data values, such as the cutting tool's velocity and acceleration. It also reads values like pressure applied to the workpiece, voltage, and current at the input and output sides.

These readings are forwarded to a standard base station (BS) in JSON format. The CNC machines are controlled using actuators, which are further controlled by the programmable logic circuit (PLC) or any other controller which can interface with the layer above. The data accumulated on the BS is then forwarded to the upper layer (i.e.; local area network (LAN) server solution layer). The physical layer also connects to the BC layer in a bidirectional way to authenticate the users operating CNC through registration and storing the important data such as the tool wear condition immutably over BC with the help of SC.

B. LAN server solution

The second layer of the model is the LAN server solution layer, which is connected with the physical layer through IoT. It handles the storage of data collected from the physical layer. Several open platform connections unified architecture (OPC UA) servers are set up for each different machine. These OPC UA servers are vendor-neutral and can communicate with different devices, transmitting and receiving data with OPC UA drivers [15]. The benefit of applying the OPC UA protocol is that it requires less expertise and can be easily set up. The controllers in the physical layer are given a tag name and register values, which are used to collect data in the OPC UA server in this layer. This layer provides a bidirectional data flow as it can send and receive data from both layer 4 and layer 5. The data transferred to layer 3 is in XML format.

C. Preprocessing Layer

The data received from layer 2 is raw in form and contains a lot of noise and redundancy. The conversion of this raw data into meaningful information is the main functionality of this layer. Several OPC UA clients are managed, which subscribes to the OPC UA servers in layer 2 to get the data. This data is then processed, and noise and data redundancy are removed. This information is passed to layer 4. The main functions of the preprocessing layer are to reduce the amount of data to send by removing unwanted data; redundancy, compressing the data to reduce the size, and thus to increase bandwidth efficiency, and to provide security for data transfer.

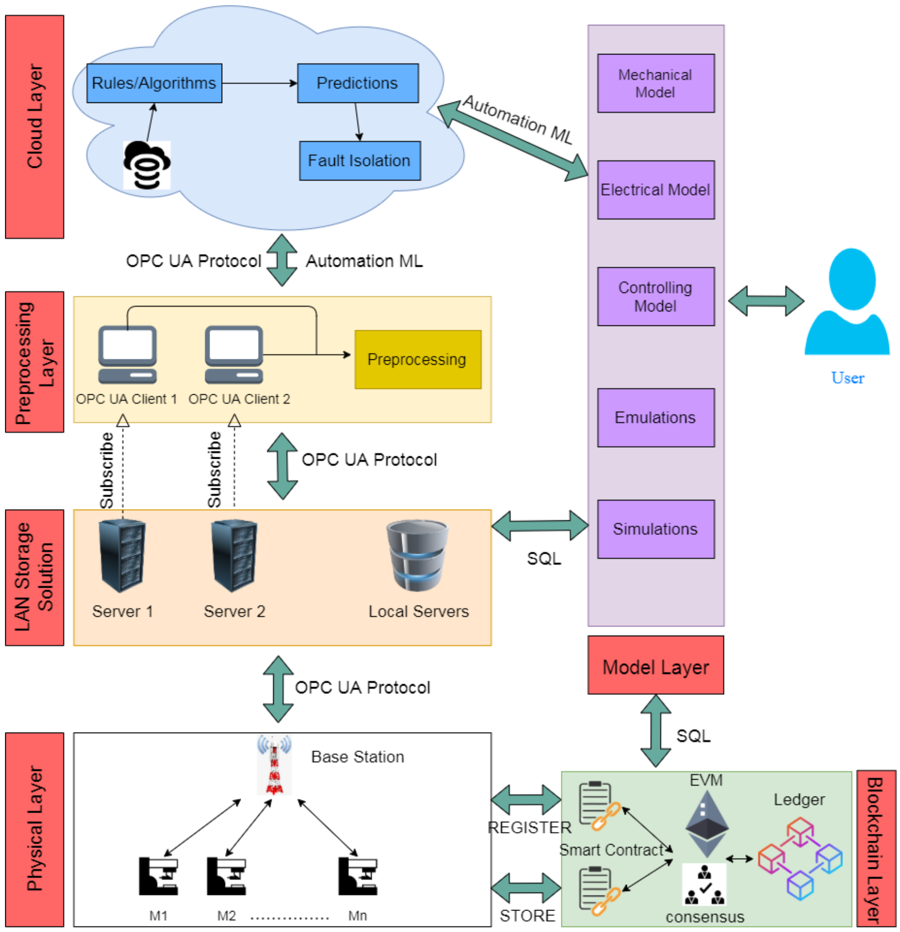


Fig. 1: Proposed six-layered architecture for DT for CNC machine

D. Cloud Layer

This layer provides cloud-based services to the data received from layer 3 and layer 5. Received data is stored and processed using various data processing techniques. These data are then stored in different repositories based on different stakeholder needs. Moreover, different machine learning algorithms are deployed to train the models in layer 5 and predict certain outcomes. These algorithms also provide the best parameters to set in CNC machines which can boost their performance. The data is sent from trained models to layer 5 through the Automation ML protocol. After predictions, fault isolation is done to abstract the fault in the CNC machines present in the physical layer [16]. The proposed algorithm is deployed on the cloud, which will help predict the CNC machines' tool condition. Algorithm 1 describes the proposed novel ensemble voting classifier. We have included three different classifiers in the ensemble voting algorithm to build a hybrid model. To understand the algorithm in general sense, let the individual classifier be denoted by l_k, which outputs an n-dimensional vector $(l_k^1(x), ..., _k^n(x))^T$ for the instance x_j, where $l_k^j(x_j) \in [0, 1]$ can be regarded as the posterior probability $P(c_i|x_j)$. Here, *i=1,2,3 j=1,2,...m*, where *i* specifies the classification algorithm, and number of samples is shown as *m* [17].

Each classifier is assigned a weight due to unequal performance and to make the voting classifier better. The combined weighted output of class c_i is calculated as follows,

$$L^j(x_j) = \sum_{k=1}^{T} \omega_k l_k^j(x_j), \tag{1}$$

where ω_k is the weight of the classifier l_k. After this, the output class label is decided by the classifier with the maximum probability is calculated as follows.

$$\widehat{y}_j = \arg\max_c [L^j(c_0|x_j), L^j(c_1|x_j)], \tag{2}$$

where c_0, c_1 are classes (i.e., tool condition wear or not).

E. Model Layer

The fifth layer of the architecture is the model layer or the 'cognition layer'. In this layer, different models such as the controlling model, electrical model, mechanical model are built for various components of manufacturing machines. These models are build using other CAD Softwares available in the market. This layer can communicate to layers 2,4 in a bidirectional flow of data. The data from the second layer is mapped using SQL. This mapped data is given to these designed models, which use this data to simulate CNC machines' present condition.

Process planning data is received from layer 5 through the automation Ml protocol. This data sets the virtual model parameters and simulates different cases to optimize the output, process planning, and increase efficiency. The simulations'

Algorithm 1 Ensemble voting based tool wear prediction

Input: D_{cnc},L_{class},D^{l}_{cnc},$cnt(D^{l}_{cnc})$,$cnt(class)$,W^{l}_{class}
D_{cnc}: CNC mill Dataset with labels representing 2 classes
L_{class} : Learning Classifiers (XGBoost, RF, AdaBoost)
D^{l}_{cnc}: Labels of training dataset
$cnt(D^{l}_{cnc})$: Number of Labels used
$cnt(class)$: Number of classes
W^{l}_{class}: Weights of each classifier in L
Output: Tool Condition T_c, $T_c \in$ (0: 'unworn', 1: 'worn')

```
procedure ENSEMBLE_VOTING(D_cnc, L_classifier, W^l_class)
    set cnt(D^l_cnc) ← 3
    set cnt(class) ← 2
    for i ← 1 to count(D^l_cnc) do
        1. Call L_n from L.
        2. Train model L_n.
        3. Predict and store the result in Pred_Test_i.
        4. Compare(D^l_cnc,Pred_Test_i.)and store the Probability in Prob_ij for each
        class and each model.
    end for
    for i ← 1 to cnt(class) do
        set sum ← 0
        for j ← 1 to cnt(D^l_cnc) do
            Weighted_Prob^i_j = W^i_j * Prob_ij
            sum ← sum + Weighted_Prob^i_j
        end for
    end for
    if Average_Prob^1 ≥ Average_prob^2 then
        T ← 0
    else
        T ← 1
    end if
end procedure
```

result is passed down to layer 4 to reinforce and predict the correct outcomes. These predicted outcomes are then passed down to layer 2, from where it is further passed to layer 1. Also, the BC layer is connected where these results are stored for transparency and traceability. A separate user interface is provided through which the user can access these 3D models.

F. BC Layer

The BC layer is embedded with the physical and model layer of the proposed architecture. In large-scale industries, there are several clusters of CNC machines located under different teams. Hence, the data integrity of the DT is crucial. All the CNCs are registered into the decentralized network through the user interface into SC to ensure this. We have used the Ethereum public BC as DT data is stored in a distributed way and it provides transparency and accountability in the system. The partial derived data such as tool wearing when classified true is also stored into the BC for traceability [18]. In Fig. 1, the BC layer is shown connecting to the physical and model layer. In this layer, there are SCs developed using solidity language. These self-executed programs interact with the physical layer's user interface for users to register the CNC machines when they are connected to DT first time [19]. The Ethereum virtual machine compiles these SCs, and through the proof of work, the consensus is achieved in the BC. All the transactions are stored immutably into the distributed ledger in BC. In this manner, the BC layer is responsible for data authentication through registration and immutably storing the data for tracking DT data history and ensuring transparency as anyone can check the transactions stored over the ledger in a decentralized way.

III. Performance Evaluation

A. Experimental setup

1) Dataset Description: The dataset was taken from Kaggle (CNC Mill Tool Wear) [20]. At the University of Michigan, multiple experiments were run on a 2" x 2" x 1.5" sized wax block in a CNC machine. Machining data was collected for variations of feed-rate, tool condition, and clamping pressure. A total of 18 experiments were performed and time-series data was collected with a sampling rate of 100 ms. Out of 18 experiments, ten experiments were run with a worn tool, while eight were run with an unworn tool. The experiments recorded the position, velocity, acceleration of parts in four motors in the CNC machine, i.e.; x-axis, y-axis, z-axis, and spindle. Input and output voltage, current, and power were also recorded. A total of 52 features and 25286 rows were recorded.

2) Developing the model: The dataset was split into two parts, i.e., 80% for training and 20% for testing. We used an ensemble approach, i.e., a voting classifier. For the voting classifier, we have used the standard sci-kit library. Three different models, namely, AdaBoost, RandomForest, and XGBoost, were used in the voting classifier to make a hybrid model. A soft voting approach was taken wherein the probability of the models used was summed up, and the maximum probability was chosen to predict the result. Weights were applied to these models according to their respective performance. AdaBoost has been given more weight than the other two as it was more accurate than others.

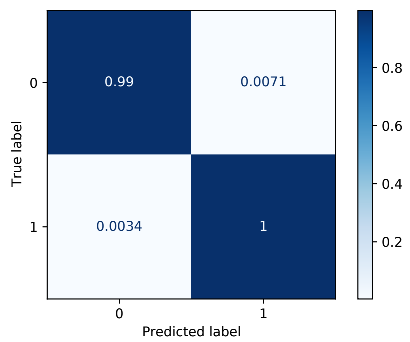
B. ROC curve

ROC curves are the classification curves that are used as a trade-off between specificity and sensitivity. It shows the performance of the model at different thresholds. The curve is plotted between the y-axis and x-axis as True Positive Rate and False Positive Rate. The roc curve of our model is shown in Fig. 3. The curve shows over the span of thresholds ranging between 0 to 1; our model has a true positive rate of near to 1 with a minimum false positive rate of around 0. This is because our model can classify the tool condition as accurately as possible. The area under the curve (AUC) is 0.99. This shows that our model can distinguish between the worn and unworn classes more precisely.

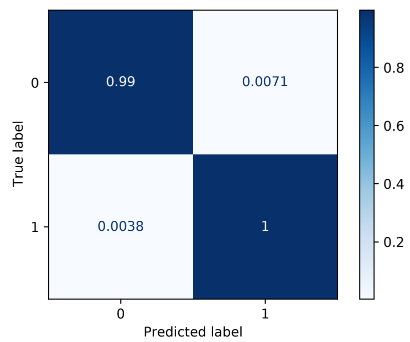
C. Confusion matrix

The confusion matrix is a layout of tables used for visualizing the performance of an algorithm. In Fig. 2, each confusion matrix table consists of two rows and two columns that relay the count of true positives, false positives, true negatives, and false negatives. To examine the results in detail, accuracy itself is not sufficient. For example, consider that our data consists of 95 worn samples and 5 unworn samples. The model classifies all the samples as worn, and thus our accuracy would be 95%, and our sensitivity (recognition rate) for worn samples would be 100%, but for unworn, it would be 0%. To find out this phenomenon in a model, the confusion matrix is important to understand.

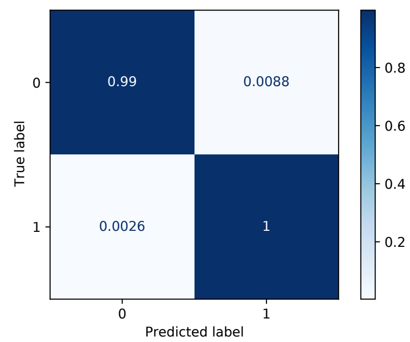
- True Positive (TP): these are the cases where the samples are unworn and our model predicted them correctly as unworn.
- True Negative (FP): these are the cases where the samples are worn and our model predicted them falsely as unworn.
- False Positive (FN): these are the cases where the samples are worn and our model predicted them falsely as unworn.
- False Negative (TN): these are the cases where the samples are worn and our model predicted them correctly as worn.



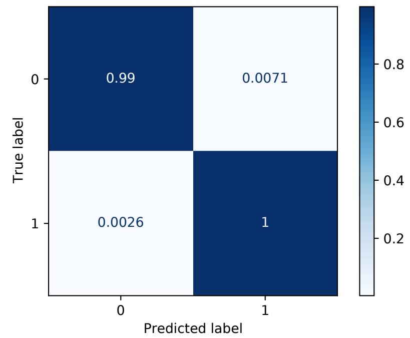
(a) AdaBoost classifier



(b) RMF classifier



(c) XG-Boost classifier



(d) Ensemble classifier

Fig. 2: Normalized confusion matrix comparison of proposed ensemble classifier with traditional classification models.

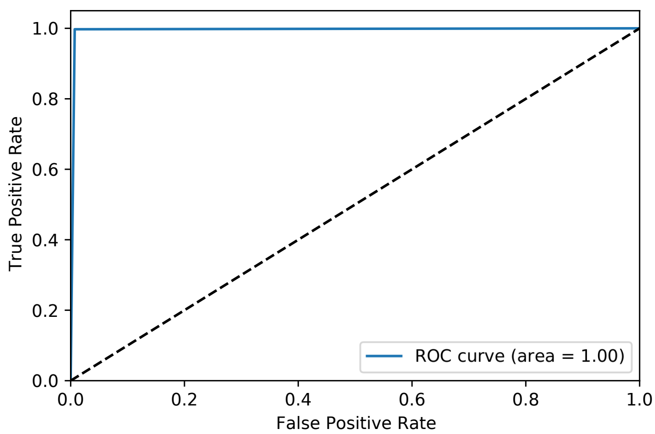


Fig. 3: ROC curve of proposed approach with ensemble learning.

The matrix's values can be normalized to get a better visualization if the dataset is huge and the number of samples is big. 2 shows the normalized confusion matrix of our model, where 0 indicates unworn samples, and 1 indicates worn samples.

D. SC implementation interface

The proposed scheme's SC is developed using solidity language and then compiled in the Remix Integrated Development Environment for the test, debugging, and simulation [21]. The Ethereum Virtual Machine compiles the code into bytecode. It is then published in the local environment of the remix. Fig. 4 shows the SC interface for the proposed approach, which shows the functions developed for traceability and authorization of stakeholders (i.e., machines and users).

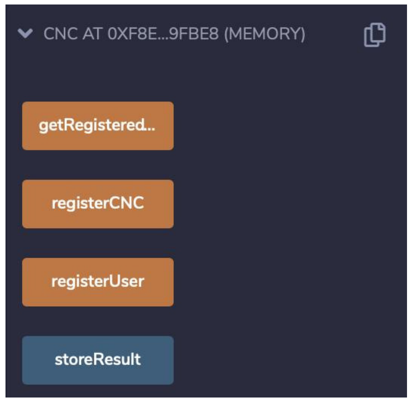


Fig. 4: SC interface using Remix IDE.

E. Prediction evaluation parameters

We have further assessed our model on the following three parameters as shown in Table I.

The recall is the ratio of the true positives to the number of true positives plus the number of false negatives. It is the measure of the correctly identified positive cases from all the actual positive cases.

$$recall = \frac{TP}{TP + FN}. \quad (3)$$

Considering Table I, our model has good recall as compared to the other three models. Our model is better at sensing the correct label.

Precision is the ratio of the number of true positives divided by the number of true positives plus the number of false positives. It is used as the measure of the correctly identified

MODEL	PRECISION	RECALL	F1 SCORE	ACCURACY (%)
XGBoost	0.9974	0.9912	0.9943	99.44
RandomForest	0.9962	0.9929	0.9945	99.46
AdaBoost	0.9966	0.9929	0.9947	99.48
Voting Classifier	0.9974	0.9925	0.9949	99.52

TABLE I

positive cases from all the predicted positive cases. Precision is always used with the recall to calculate the F1 score.

$$precision = \frac{TP}{TP + FP}. \tag{4}$$

Considering the Table I, our model has good precision as compared to the other three models.

The F1 score is the harmonic mean of precision and recall taking both metrics into account in the following equation:

$$F1 = \frac{2 \cdot precision \cdot recall}{precision + recall}. \tag{5}$$

The harmonic mean is used to remove the influence of extremes. A simple average in precision equals 1, and recall equals 0 leads to an F1 score of 0.5, while the harmonic mean leads it to 0, thus giving equal importance to both precision and recall. It is evident from Table I, F1 score of our model is better than the other three models. The accuracy of the proposed model is calculated as a ratio of total correct classifications to the total number of predictions during the model's testing phase.

Considering all the above-mentioned parameters in our model, it can be inferred that our model performs better considering accuracy and F1 score. This shows that our model is correctly trained and avoids over-fitting.

IV. Conclusion

We have proposed a six-layered architecture in this paper for the DT-based CNC mill solution, which incorporates AI, BC, and various other protocols. Moreover, we have implemented an ensemble voting classifier as part of the cloud layer algorithm. The algorithm uses three models, namely XGBoost, Random Forest, and AdaBoost, and predicts the classification of the CNC milling tool if its condition is wearing or not. Also, the BC layer is introduced to maintain trust, transparency, and security of DT data using public Ethereum BC. The prediction models are trained and then its performance evaluation is done based on accuracy, F1 score, precision, and recall. The proposed scheme has an accuracy of 99.52%. In the future, the scalability of the proposed approach on different BC platforms can be verified.

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