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2023-2 Mechatronics Integration Project

# **Basic Research on Steel Type Distinction Technology Based on Spark Video**

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## 1. Introduction

### Problem Definition

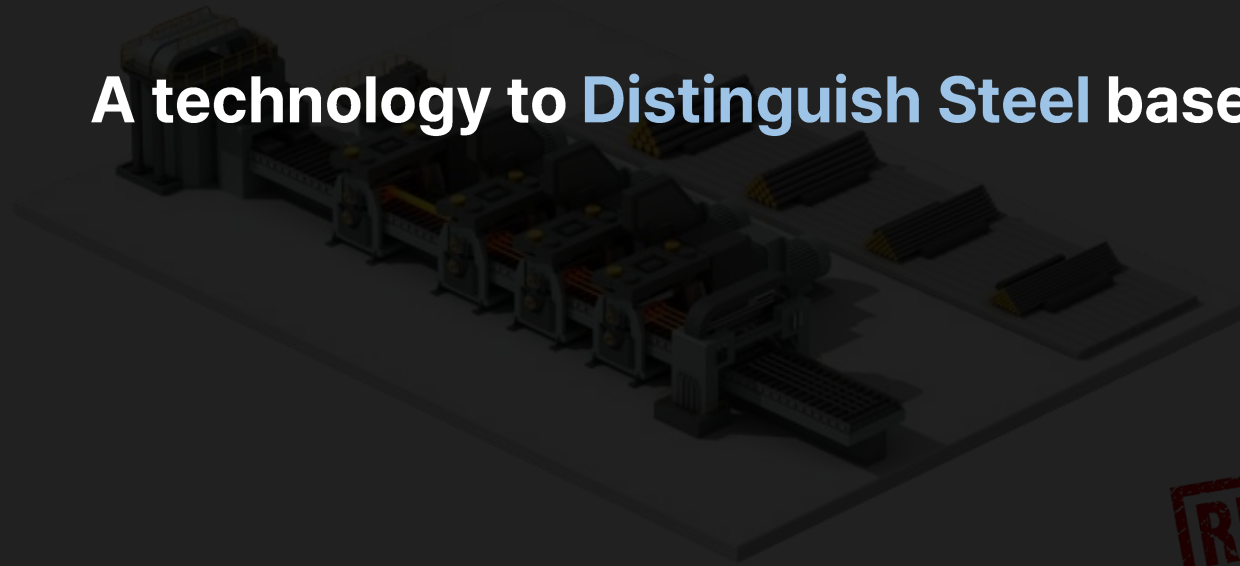


### Problems with inspection equipment

1. **Expensive** inspection equipment  
(More than **100 million ₩**)
2. Distinguishes **different metal**,  
but **not carbon content** in steel



**A technology to Distinguish Steel based on Carbon Content is necessary**



Steel bar Rolling Process



C55 Steel



C35 Steel



C20 Steel



- Mixing steel in **continuous process** causes **mass recalls**
- Severe **Economic Losses**

# 1. Introduction

How Can We Distinct Based on Carbon Content?



Spark Test

## What is Spark Test?

- A technique to **distinguish steel types** through the different **spark shapes** generated by various metal materials
- Skilled experts are capable of distinguishing these **visually**



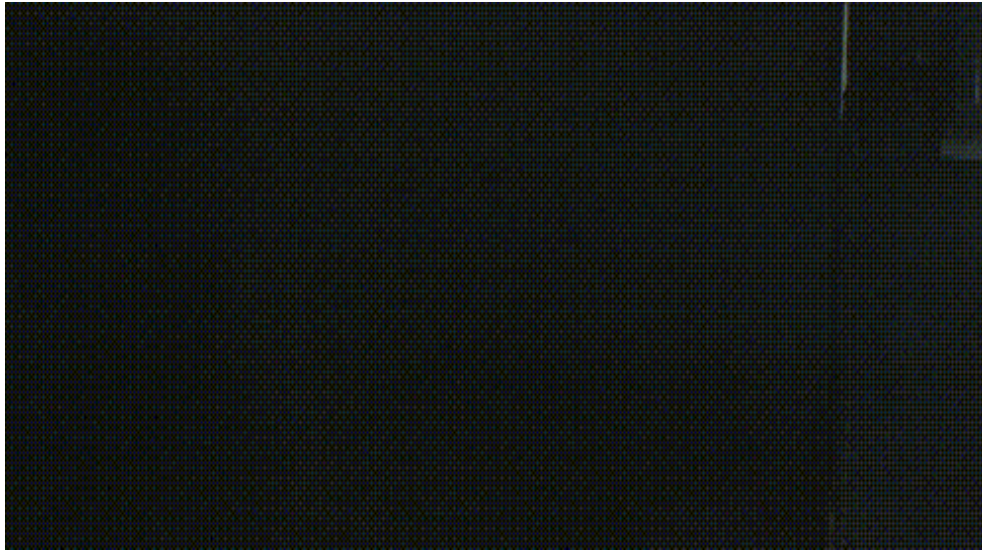
Development of a **steel classification** algorithm based on **spark characteristics** through image processing

**Incidents of mixed steel types can be prevented**

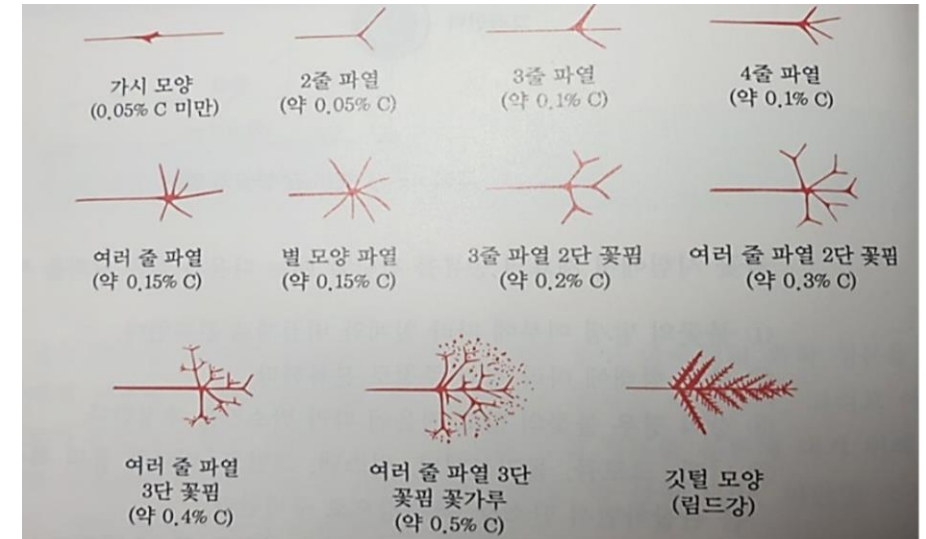
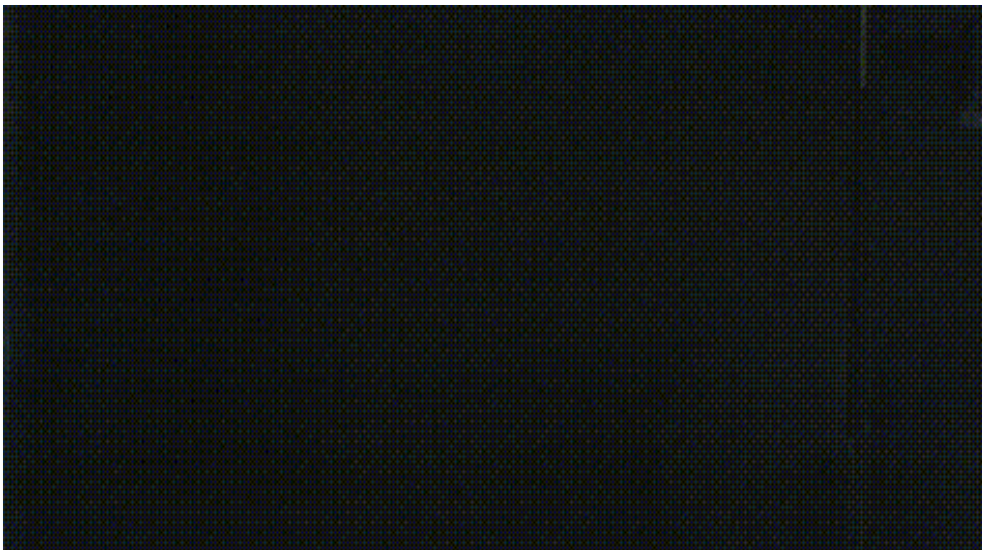
# 1. Introduction

## Spark Characteristics according to Carbon Content

0.1% Carbon



0.55% Carbon



Burst shape depending on carbon content



0.1% Carbon



0.35% Carbon



0.55% Carbon

As the carbon content **increases**

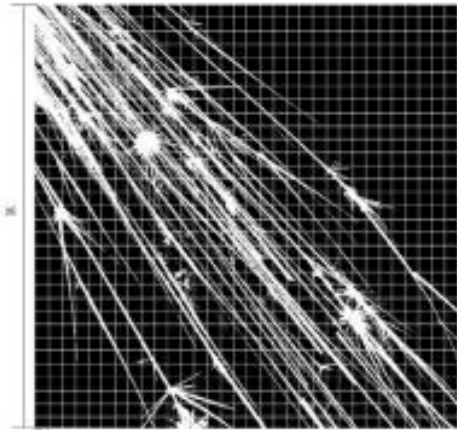
- The number of **exploding branches** increases
- The **length of the spark** shortens
- **Brighter** light is emitted



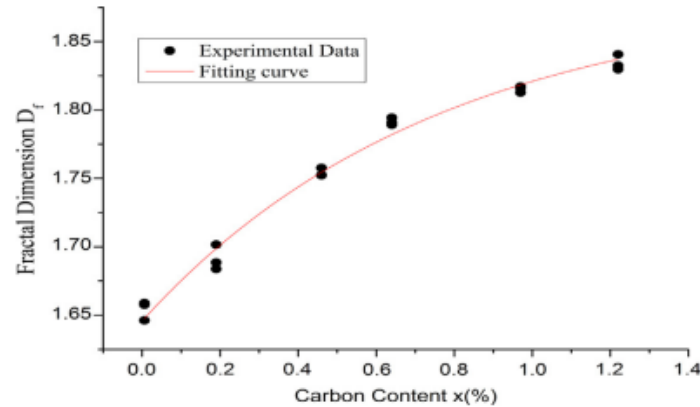
# 1. Introduction

Paper 1

**Spark testing to measure carbon content in carbon steels based on fractal box counting**



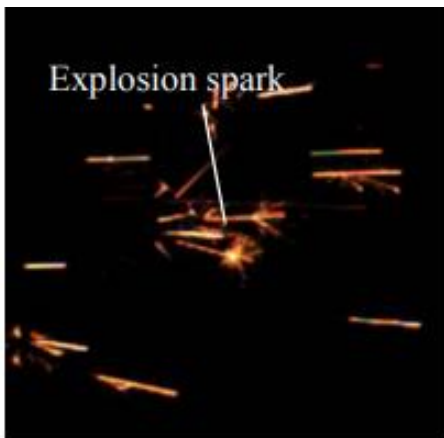
Fractal box counting



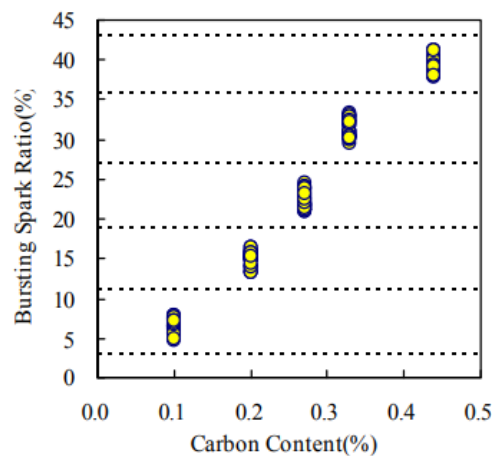
- Does not reflect **spark characteristics** according to **carbon content**
- **Not** applicable in **real-time**
- The **gap in carbon content** is more than 0.1%

Paper 2

**Development of Automated Spark Testing Technique by Image Processing to Measure Carbon Content in Steel Materials**



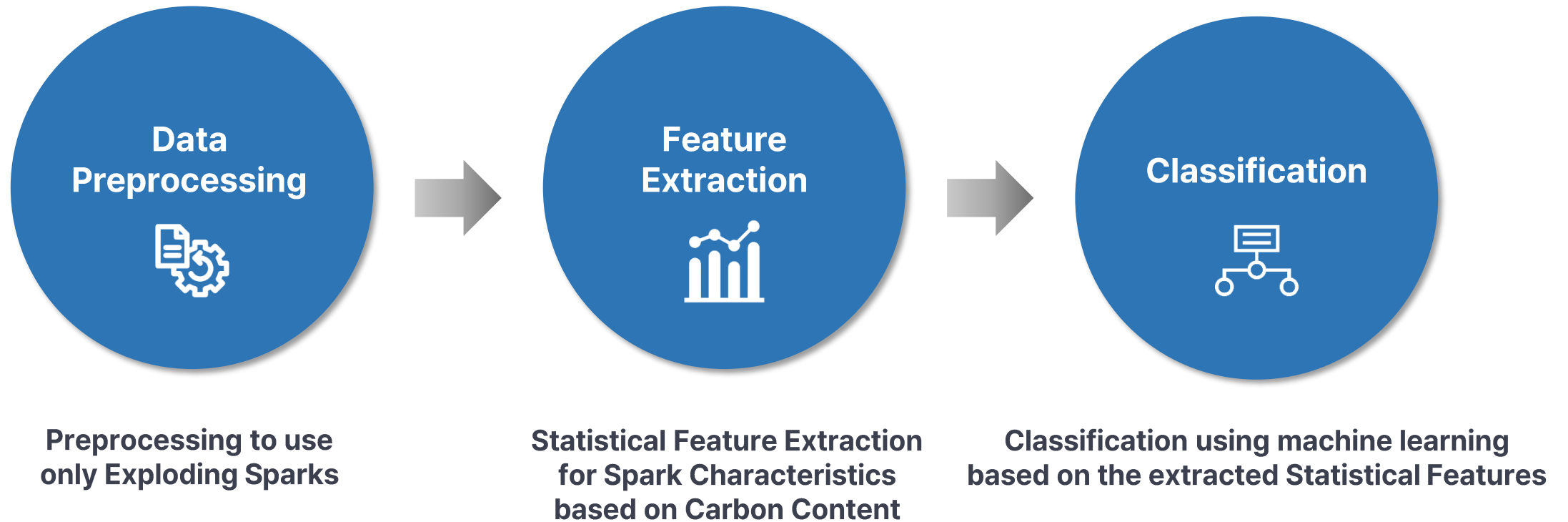
Explosion spark ratio



↔ Distinguishing steel types  
with a carbon content gap within 0.1%

📺 verifying real-time applicability  
by proceeding with video instead of images

## 2. Research Flow



3. Research Process : Data Preprocessing → Feature Extraction → Classification

Method 1  
Spark Area  
Detection



Advantage

- A relatively **lightweight algorithm**
- Capable of detecting **explosion spark** areas

Disadvantage

- **Stem sparks** other than explosion sparks are also detected
- The **accuracy decreases**

Method 2  
Streamline  
Elimination



Advantage

- Only the point of **explosion** can be detected

Disadvantage

- Significant **impact of parameters**
- **Data loss** occurs

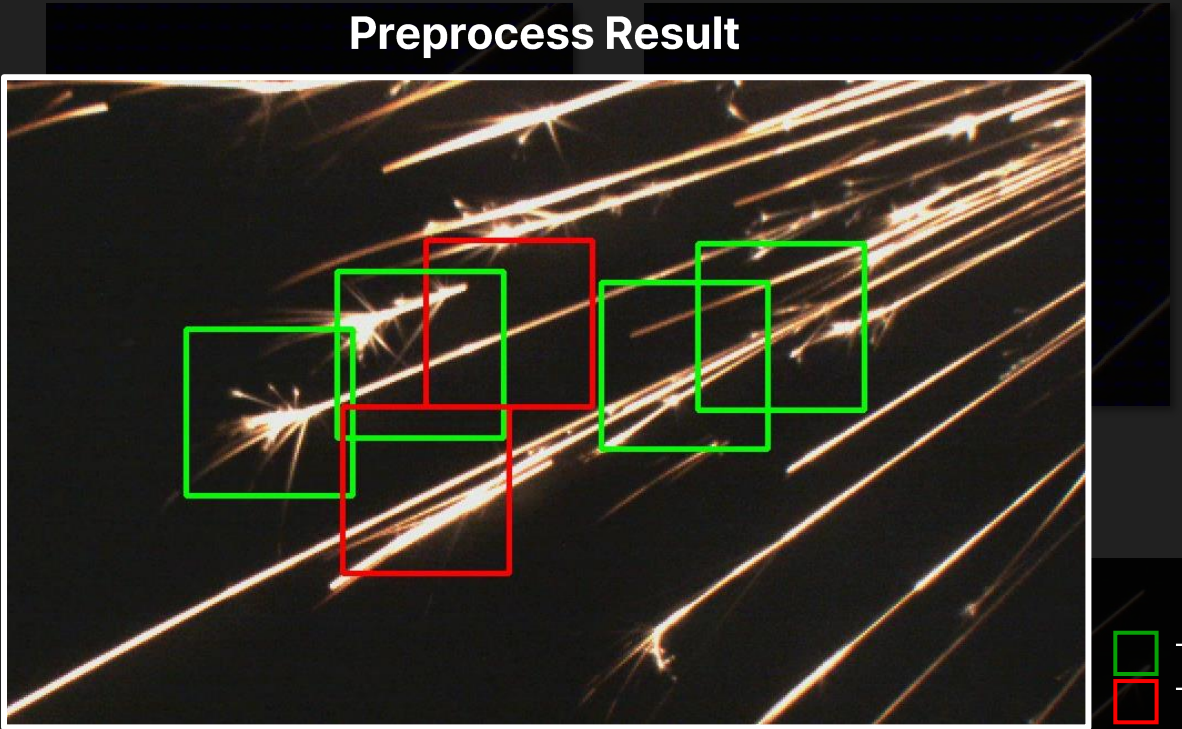
\* Above image is enhanced visibility through color inversion

3. Research Process : Data Preprocessing → Feature Extraction → Classification

Method 1 : Spark Area Detection



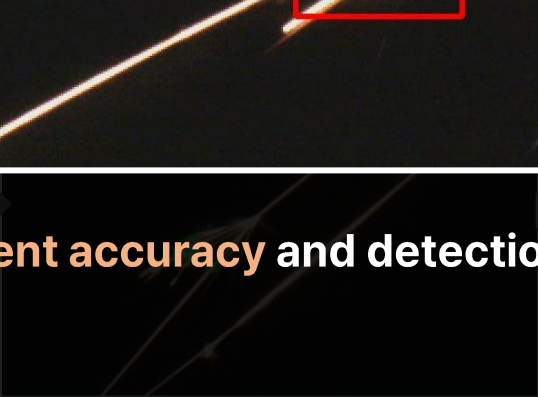
Original Spark



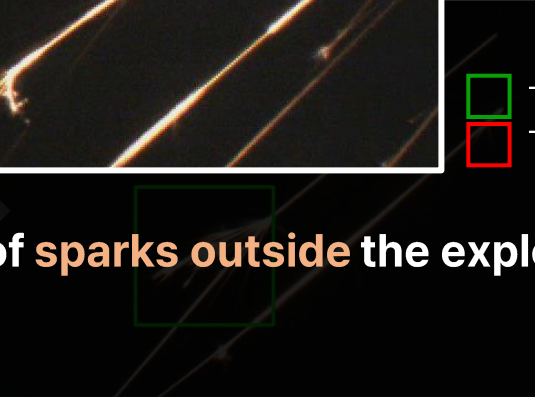
Preprocess Result



Detection of abnormal PCA values



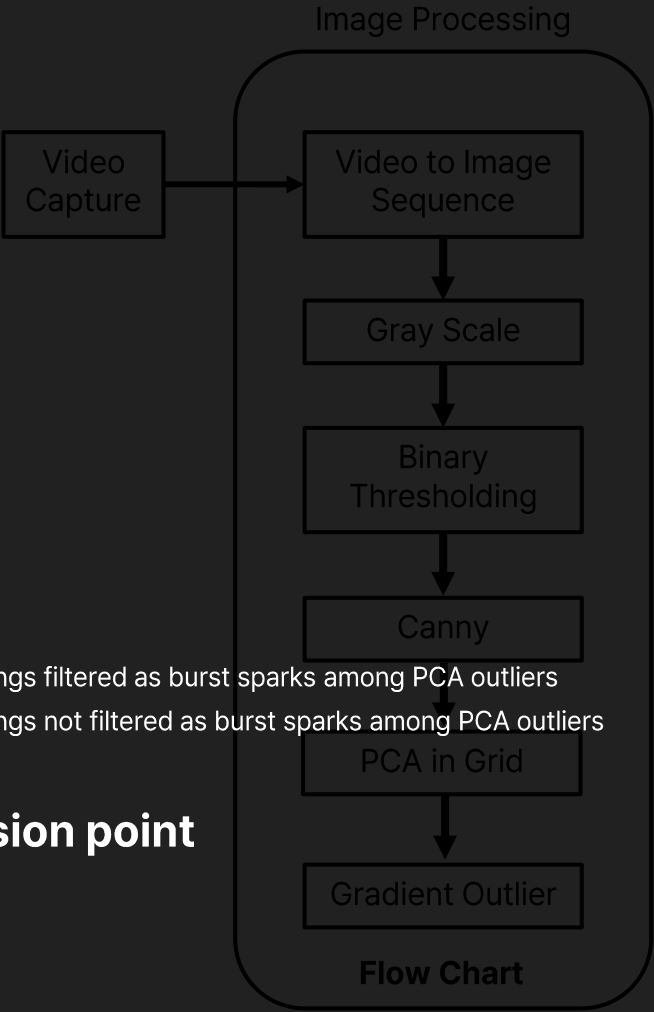
Detecting abnormal PCA values of the explosion point with DBSCAN



Detect as explosion spark when a certain number of clusters are satisfied

Insufficient accuracy and detection of sparks outside the explosion point

- Things filtered as burst sparks among PCA outliers
- Things not filtered as burst sparks among PCA outliers





### 3. Research Process : Data Preprocessing → Feature Extraction → Classification

Method 2 : Streamline Elimination



0.1% Carbon

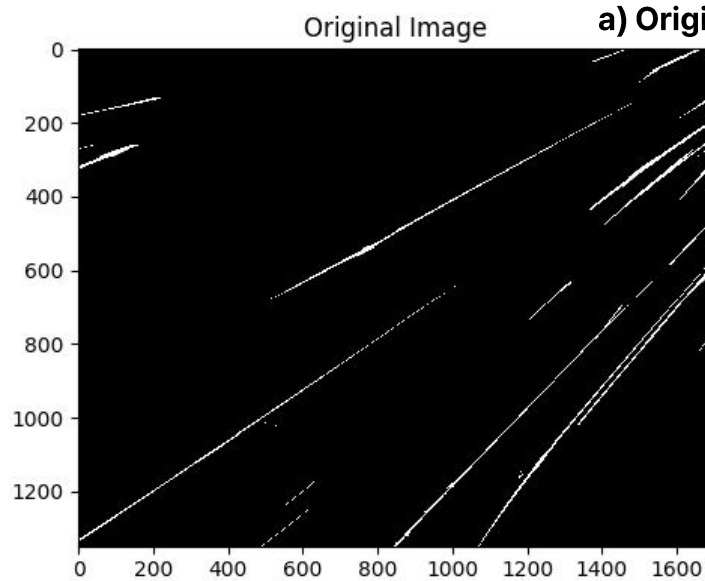
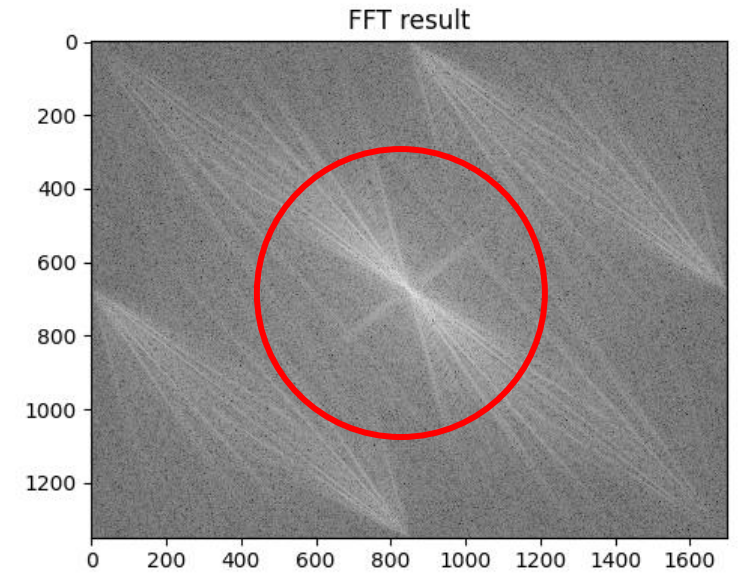
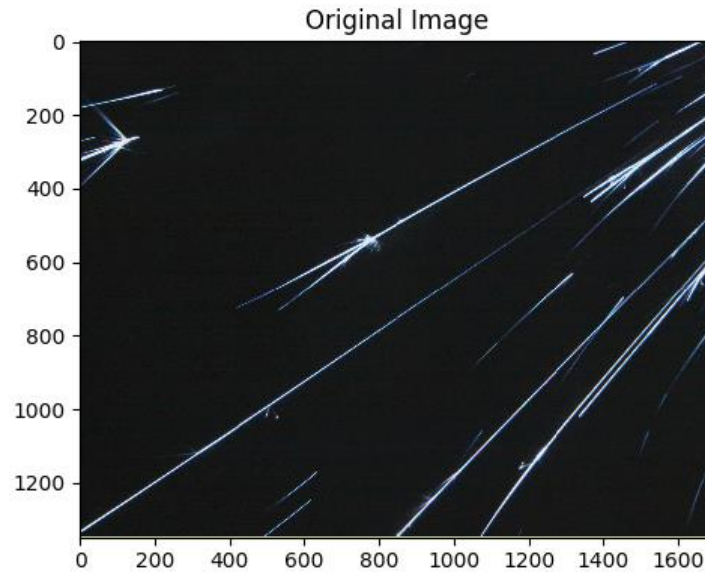


0.35% Carbon

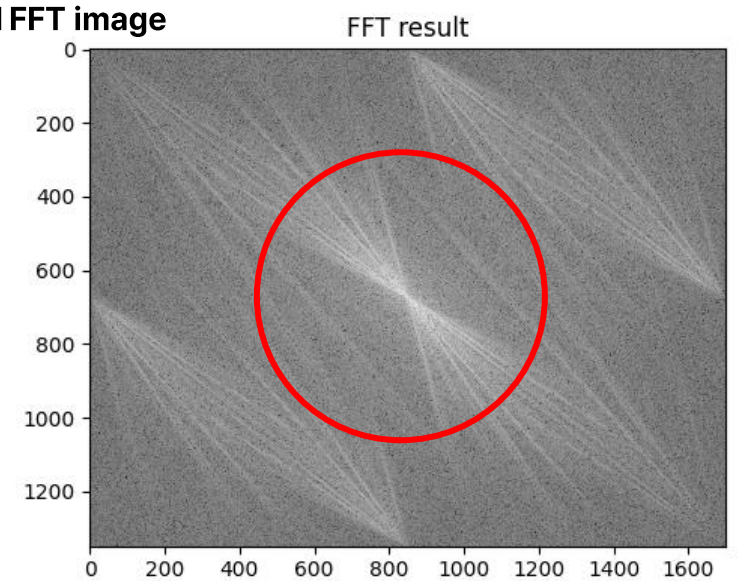
As the **carbon content increases**, the number of explosion spark **branches increases**  
(Rapidly Changing Points)



**Filtering** only data of exploding points  
using **High Frequency** areas



a) Original FFT image



b) FFT image with explosion spark deleted

### 3. Research Process : Data Preprocessing → Feature Extraction → Classification

Streamline Elimination

FFT Image

IFFT Image

Image Processing

Raw Spark Image

Filtering with Exploding Spark



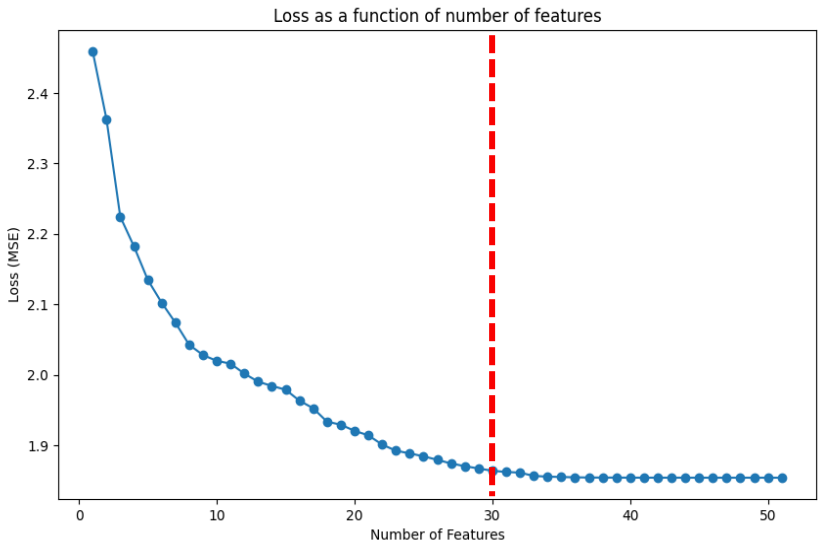
Filtering primarily on data from Exploding spark points

IFFT

Flow Chart

Recover FFT components of exploding spark

3. Research Process : Data Preprocessing → Feature Extraction → Classification



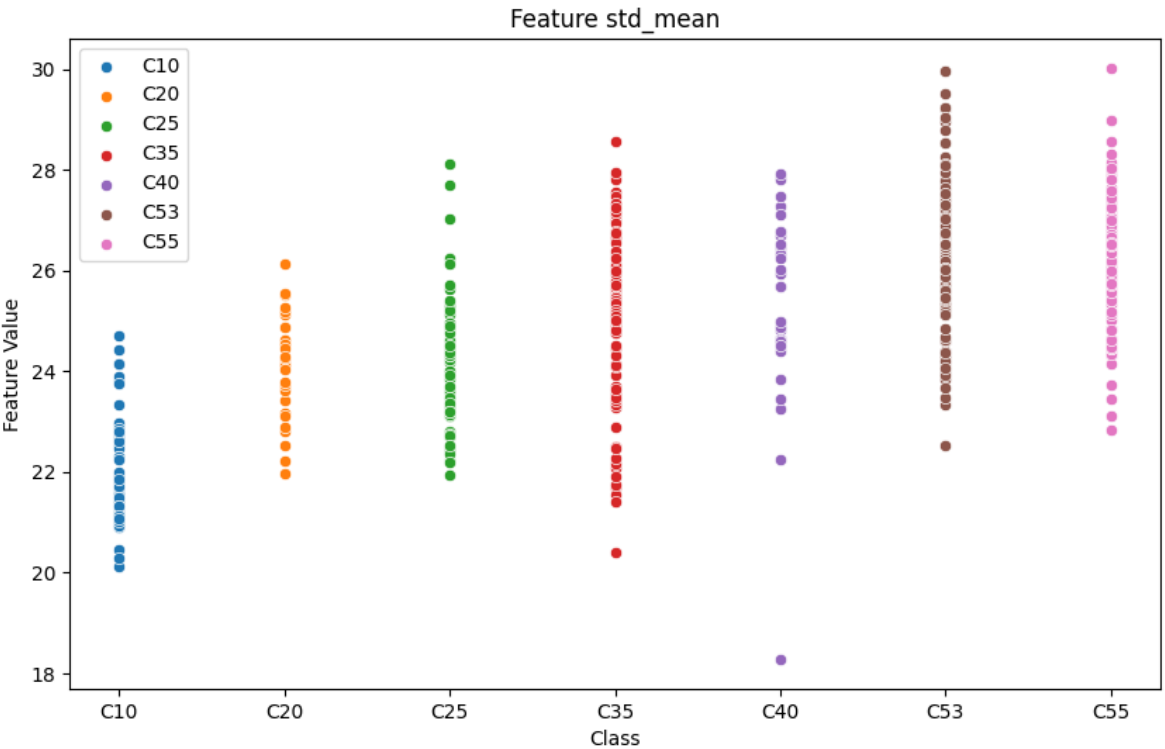
Optimal learning determined at **30 features** based on MES loss



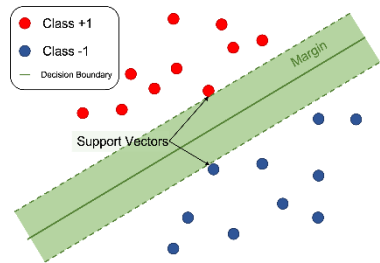
SFS

(Sequential Forward Selection)

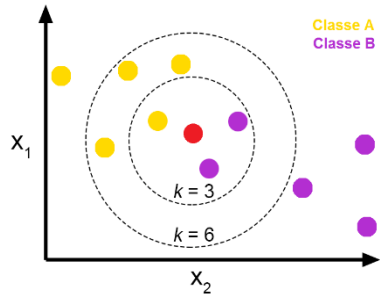
Selecting **30 Features** that Well Represent  
the **Characteristics of Steel**



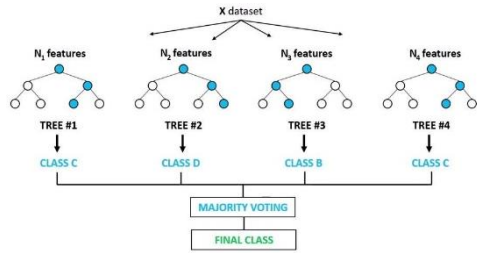
3. Research Process : Data Preprocessing → Feature Extraction → Classification



SVM



KNN

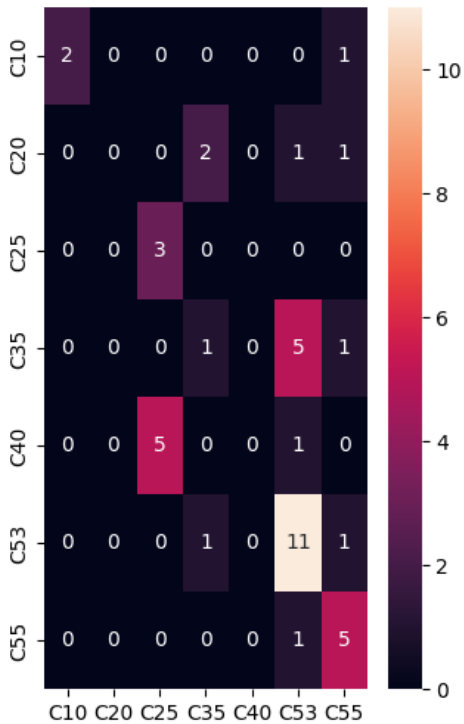


Random Forest

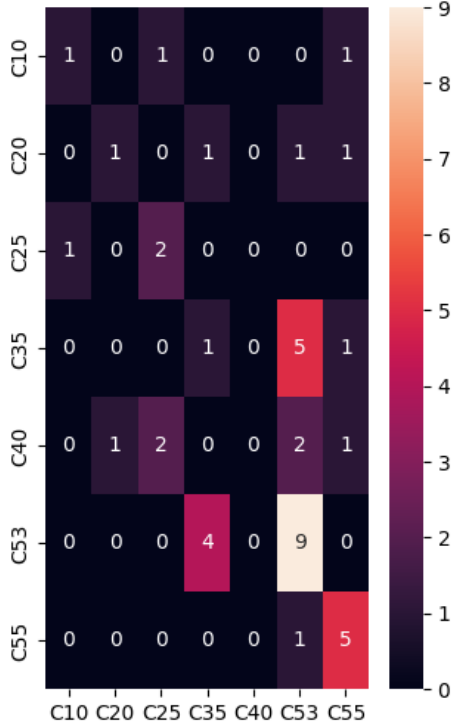
	SVM[%]	KNN[%]	Random Forest[%]
Accuracy	52.38	45.24	57.14
Precision	63.59	51.67	59.42
Recall	53.38	45.23	57.14

Classification Results Table

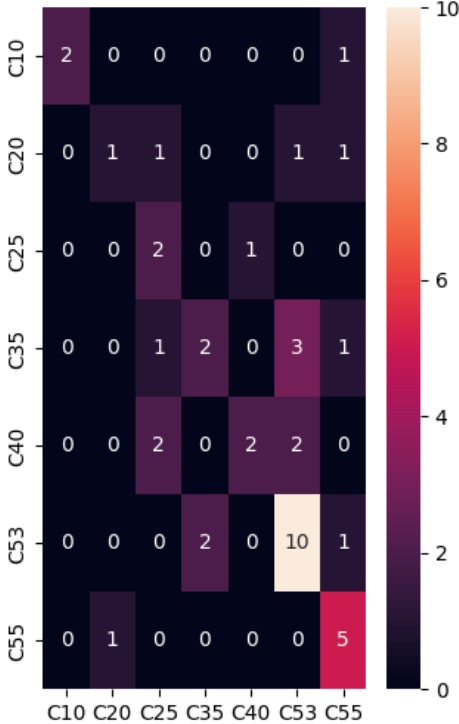
SVM Confusion Matrix



KNN Confusion Matrix



Random Forest Confusion Matrix



Reason for Low Accuracy

- Due to the **lack** of the **Test set**, the **accuracy is lower**
- With **more** classes in the **Test set**, **accuracy improves**



Difference in Performance Between Models

- **SVM** excels with high-dimensional data due to its **complex decision boundaries**
- **Random Forest** is adept at learning complex patterns due to its **random feature selection**

## 4. Result

↔ Distinguishing classes **above 0.1% was possible**, but **accuracy dropped** below that due to **data shortage**

📺 Since features were extracted and learned **from the video**, it is expected to be applicable in **real-time** videos as well

### Case Specifications



0.1% Carbon



0.35% Carbon

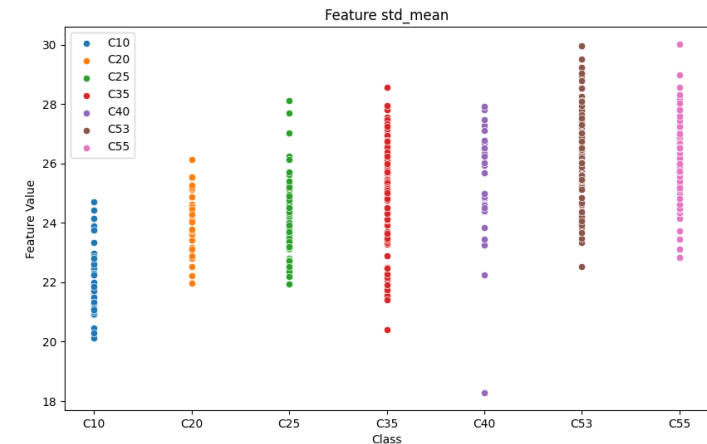


0.55% Carbon

The number of **Exploding Branches** increases



### Feature Selected

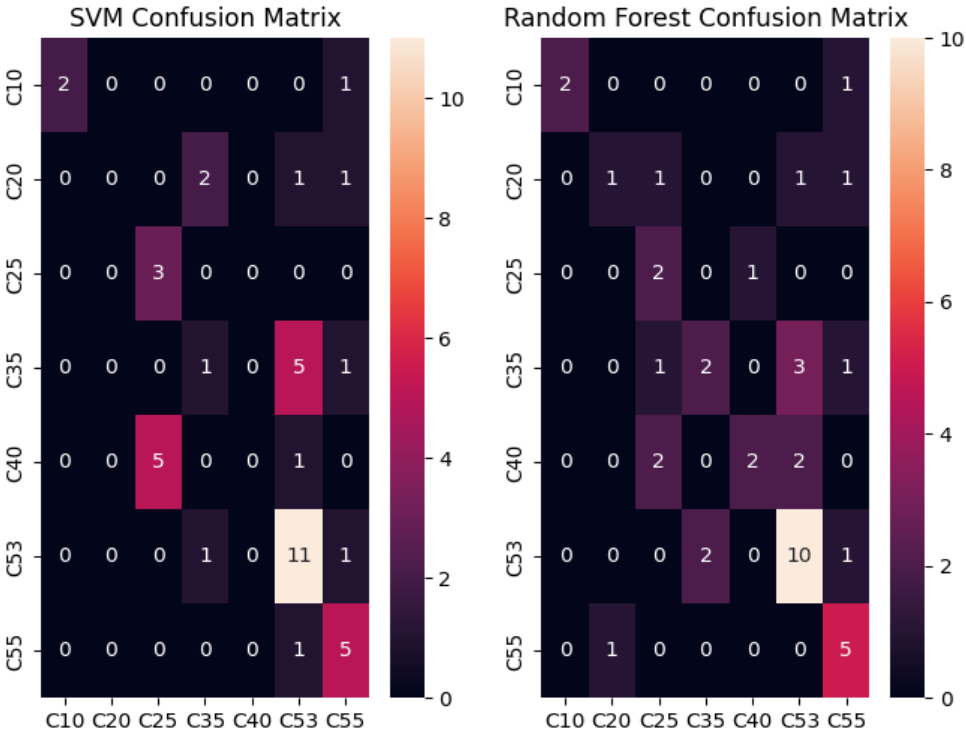


Top features, reflecting **Data Distribution**, include **standard deviation**, **kurtosis**, and **skewness**

**Increased carbon** leads to more **spark branches**, equivalent to **greater pixel dispersion**  
Using this **dispersion** for **steel type differentiation** improves classification performance



5. How to Improve the performance



Spark Set	C10	C20	C25	C35	C40	C53	C55
Train	1,543	914	1,804	2,764	994	3,964	3,388
Test	120	180	114	341	293	620	289

Training and Test Data Sets Used

➡ The **more data sets**, the **better the learning performance** tends to be.  
**Increasing spark data** can improve performance.

# Thank you

## Q&A

