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Dedication

I dedicate this work with great love and respect to my beloved parents, whose unconditional love, endless sacrifices, and constant prayers have always guided me toward success. They have been my source of inspiration and the reason behind every achievement in my life.

To my brothers and sisters, thank you for your support, understanding, and encouragement during every step of this journey. Your presence in my life has always given me strength and happiness.

To my dear friends, thank you for standing by my side during both good and difficult times. Your loyalty, kindness, and motivation will always be appreciated and remembered.

I also dedicate this work to my teachers and mentors who shared their knowledge and inspired me to continue learning and growing.

Finally, this dedication goes to everyone who believed in me, encouraged me, and helped me become the person I am today. This achievement belongs not only to me, but also to all those who supported me with love, trust, and sincere encouragement.

Thanks

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Finally, I thank God for giving me the strength, patience, and determination to complete this work successfully.

ملخص

يركز البحث على تشخيص أعطال زيوت المحولات الكهربائية باستخدام تقنيات الذكاء الاصطناعي وخوارزميات التعلم الآلي مثل "الغابات العشوائية". يستعرض العمل الخصائص الكيميائية والفيزيائية للزيوت العازلة، وآليات تدهورها، مع مقارنة بين الطرق التقليدية للتحليل الكروماتوغرافي والأساليب الحديثة القائمة على الرؤية الحاسوبية. كما يتضمن الجانب التطبيقي تجارب مخبرية لقياس جهد الانهيار وتطوير نظام آلي للتنبؤ بحالة الزيت بناءً على سمات الصور المستخرجة. تهدف الدراسة في النهاية إلى دعم الصيانة الاستباقية وتعزيز استقرار الشبكة الطاقوية الوطنية بكفاءة اقتصادية عالية.

الكلمات المفتاحية : المحولات الكهربائية– الذكاء الاصطناعي– الغابات العشوائية

Summary

This research investigates the automated fault diagnosis of electrical transformer insulating oils through the application of artificial intelligence (AI) techniques and machine learning (ML). The study presents a comprehensive examination of the physicochemical properties of insulating oils and the underlying mechanisms governing their degradation, alongside a systematic comparative analysis between conventional chromatographic analytical methods and contemporary computer vision-based approaches. The practical component encompasses laboratory experiments designed to quantify dielectric breakdown voltage, as well as the development of an intelligent predictive system for assessing oil condition on the basis of image-derived feature extraction. The overarchin

Keywords: automated fault diagnosis- electrical transformer- artificial intelligence (AI) techniques

Résume

Cette recherche porte sur le diagnostic des défauts des huiles de transformateurs électriques à l'aide de techniques d'intelligence artificielle et d'algorithmes d'apprentissage automatique tels que les forêts aléatoires. Elle examine les propriétés chimiques et physiques des huiles isolantes et leurs mécanismes de dégradation, en comparant les méthodes d'analyse chromatographique traditionnelles aux techniques modernes de vision par ordinateur. La partie appliquée comprend des expériences en laboratoire pour mesurer la tension de claquage et le développement d'un système automatisé de prédiction de l'état de l'huile à partir des caractéristiques extraites des images. L'objectif final de cette étude est de favoriser une maintenance proactive et d'améliorer la stabilité du réseau électrique national de manière rentable.

Mots-clés: diagnostic des défauts des huiles- transformateurs électriques- techniques d'intelligence artificielle

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GENERAL INTRODUCTION

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Power transformers are among the most strategically critical assets in electrical transmission and distribution networks. Their continuous and reliable operation is indispensable to the stability of modern power systems, which serve as the backbone of industrial, commercial, and domestic energy supply. Any unplanned outage or catastrophic failure of a transformer not only incurs substantial economic losses but may also compromise the security of entire regional grids. As the global demand for electrical energy escalates and infrastructure ages, ensuring the health and longevity of transformer assets has become a matter of paramount engineering concern.

Central to the operational integrity of oil-immersed power transformers is the insulating oil, which simultaneously performs the functions of electrical insulation and thermal dissipation. The oil provides a dielectric medium that withstands high electric fields between energized conductors, while its convective circulation facilitates the removal of heat generated by resistive and core losses. Beyond these primary roles, transformer oil plays a critical ancillary function in retarding the degradation of cellulosic solid insulation — paper and pressboard — by impregnating its fibrous structure and moderating the effects of moisture and oxidative attack.

Despite its essential role, transformer oil is not immune to deterioration. Subjected to the combined and synergistic stresses of elevated temperature, dissolved oxygen, moisture ingress, electric field exposure, and catalytic interactions with metallic and cellulosic construction materials, the insulating oil undergoes progressive physicochemical degradation. This aging process manifests as increases in acidity, dielectric loss factor, viscosity, and moisture content, accompanied by the generation of hydrocarbon and non-hydrocarbon gases and the formation of oxidation sludge. Left undetected or unmanaged, advanced oil degradation significantly reduces the dielectric strength of the insulation system, raises the risk of partial discharges and thermal runaway, and ultimately precipitates premature transformer failure.

The diagnostic assessment of transformer oil condition has therefore become an essential component of proactive asset management strategies in modern utilities. Among the arsenal of available diagnostic tools, Dissolved Gas Analysis (DGA) occupies a position of preeminence. By quantifying the concentrations of key fault gases dissolved in the oil — including hydrogen, methane, ethylene, ethane, acetylene, carbon monoxide, and carbon dioxide — DGA enables the inference of internal fault conditions such as partial discharges, low- and high-energy electrical discharges, and thermal overheating at varying temperature thresholds. Complementary physicochemical tests, including breakdown voltage measurement, acidity determination, water content analysis, and dielectric dissipation factor testing, provide additional dimensions of diagnostic information that collectively characterize the state of oil degradation and the residual health of the insulation system.

Traditional diagnostic methodologies, while robust and internationally standardized, present inherent limitations in the context of large-scale transformer fleet management. These conventional approaches are time-intensive, require specialized laboratory infrastructure and trained personnel, and necessitate physical oil sampling from energized equipment — operations that introduce logistical, safety, and scheduling challenges in field environments. The growing volume of transformers requiring periodic assessment, combined with the imperative for early fault detection before catastrophic failure occurs, has created a compelling demand for faster, more accessible, and increasingly automated diagnostic tools.

The emergence of artificial intelligence and machine learning as transformative technologies across engineering disciplines has opened new avenues for transformer diagnostics. By leveraging the pattern recognition capabilities of supervised learning algorithms — including support vector machines, k-nearest neighbors, decision trees, random forests, and deep neural networks — it has become possible to develop automated classification systems that can map DGA data and physicochemical measurements to fault categories with accuracy levels that are competitive with, and in some configurations superior to, expert-based interpretive methods. Furthermore, recent advances in computer vision have demonstrated the feasibility of extracting diagnostically meaningful information from photographic images of oil samples, offering a promising pathway toward rapid, non-destructive preliminary screening tools deployable in field conditions.

Chapter I
Insulating Oils for Power Transformers

I.1 Introduction

The increasing demand for reliable electrical energy transmission and distribution has made the use of high-quality power transformers indispensable. Insulating oils perform a dual essential function within transformers: they act simultaneously as dielectric media, preventing electrical breakdown between energised components, and as coolants, dissipating the heat generated by resistive and core losses. Numerous oil formulations have been developed to deliver superior insulating performance, with thermal and oxidative stability being the most critical selection criteria. Of all available dielectric fluids, mineral oil remains the most widely employed, owing to its well-established physicochemical properties and low cost.

This chapter presents a structured overview of power transformers and their insulating oil systems. It begins with the classification and constructional features of power transformers, proceeds to analyse fault types and their causes, examines the principal physicochemical properties of insulating oils, and concludes with a discussion of oil ageing mechanisms and the dissolved gas analysis (DGA) technique used for transformer condition monitoring.

I.2 Power Transformers

Power transformers belong to the category of static AC electrical equipment — apparatus that operates without any moving components and is therefore free from mechanical friction losses. This static nature grants them exceptional reliability and a service life spanning several decades, a longevity rarely matched by any other class of electrical machinery.

Their operating principle relies on electromagnetic induction, whereby a ferromagnetic core forms a closed magnetic circuit coupling two or more electrically isolated winding sets, enabling energy transfer between circuits at different voltage and current levels. The core material — typically grain-oriented silicon steel — possesses a magnetic permeability thousands of times greater than air, ensuring that flux is efficiently concentrated and guided through the intended path.

Frequency is strictly conserved across the transformation, being determined entirely by the supplying source. Apparent power is nominally preserved, though core and copper losses cause output to fall marginally below input, making lossless transfer a theoretical ideal. Beyond voltage transformation, the transformer provides galvanic isolation between its coupled circuits, preventing fault current conduction, suppressing interference, and serving safety and instrumentation applications.These combined characteristics establish the power transformer as the foundational apparatus of modern power systems, making high-voltage transmission economically viable and enabling the stepwise voltage reduction required to deliver power safely to industrial and domestic consumers.

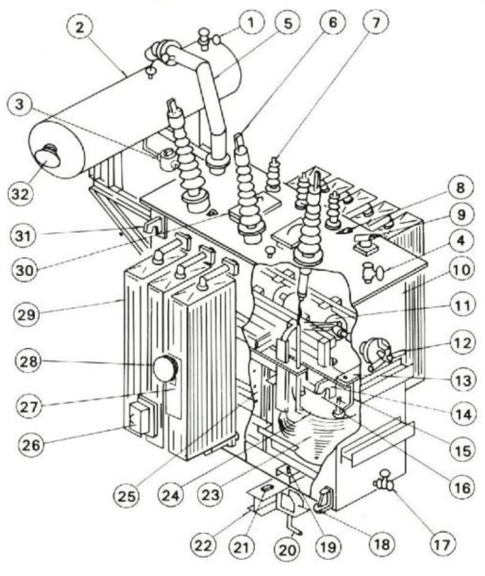

Figure I.1: View of a power transformer

The principal components of a power transformer, as labelled in Figure I.1, are enumerated in Table I.1.

Table I.1 — Power transformer components as labelled in Figure I.1

No.	Component	No.	Component	No.	Component
1	Oil filter valve	12	Tap changer handle	23	Coil
2	Conservator	13	Fastener for core and coil	24	Coil pressure plate
3	Buchholz relay	14	Lifting hook for core and	25	Core
4	Oil filter valve	15	End frame	26	Terminal box
5	Pressure-relief vent	16	Coil pressure bolt	27	Rating plate
6	High-voltage bushing	17	Oil drain valve	28	Dial thermometer
7	Low-voltage bushing	18	Jacking boss	29	Radiator
8	Suspension lug	19	Stopper	30	Manhole
9	BCT terminal	20	Foundation bolt	31	Lifting hook
10	Tank	21	Grounding terminal	32	Oil level gauge
11	De-energised tap changer	22	Skid base		

I.3 Malfunctions, Causes and Statistics

Power transformer outages rank among the leading contributors to electrical supply disruptions and pose a significant threat to network reliability. The root causes of such failures are manifold and are influenced by the prevailing operating conditions, the original design specifications, and the environmental context in which the unit operates. Transformer failures fall into two broad categories [1]:

- Forced unavailability following a major fault (winding damage, defective tap changer, etc.).
- Unplanned disconnection for repair or on-site maintenance due to progressive degradation (excessive gas production, moisture ingress, etc.).

From a technical standpoint, faults may be attributed to electrical, thermal, or mechanical phenomena, and may originate from either internal or external sources. Table I.2 provides a structured summary of the most commonly reported failure causes.

Table I.2 — Principal causes of power transformer malfunctions.

Internal Causes	External Causes
Deterioration of insulation Loss of winding tightening Overheating Solid contamination in insulating oil Partial discharges Design and manufacturing defects	Overvoltages from switching or atmospheric origin Overload conditions

I 4 Insulation Systems of Power Transformers

I.4.1 Solid Insulation

Among the solid dielectric materials employed in electrical engineering, cellulose-based products — kraft paper and pressboard — stand out as the most enduring, having been integral to oil-filled transformer design for well over a century. Their primary function is to provide reliable electrical isolation between adjacent conductors and between the energised winding assembly and the earthed tank structure. Chemically, both materials are founded on cellulose, a linear polysaccharide in which β-D-glucopyranose units are linked head-to-tail by β-1,4-glycosidic oxygen bridges, as illustrated in Figure I.2. This structural motif accounts for 40–50% of the material composition and is responsible for its mechanical rigidity and dielectric performance. Paper is particularly deployed in narrow-clearance regions of the winding insulation, benefiting from a dielectric withstand capability approximately twice that of the surrounding oil. Prior to installation, the paper undergoes vacuum thermal drying to reduce residual moisture below 0.5% by mass; subsequent immersion in transformer oil eliminates any remaining gas voids that could otherwise act as sites for partial discharge inception.

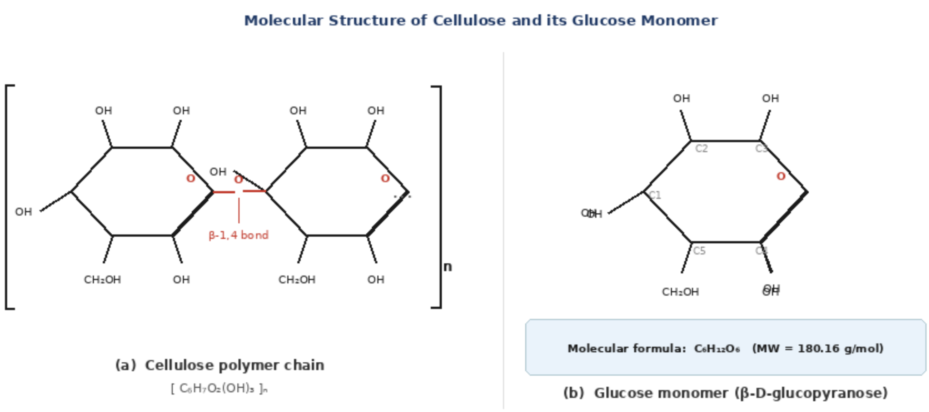

Figure I.2 — Cellulose chain and Glucose Structure

I.4.2 Liquid Insulation

The liquid insulation category covers mineral oils, vegetable-based oils, and synthetic fluids, each delivering the twin requirements of electrical insulation and thermal cooling. Among these, mineral oils hold by far the largest market share, representing approximately 90–95% of all dielectric liquid installations worldwide, a dominance explained by their combination of favourable electrical performance, well-documented physicochemical behaviour, and competitive cost. [2]

I.4.2.1 Oil Degradation and Ageing

Sustained exposure to electrical, thermal, and chemical stresses progressively and irreversibly alters the physicochemical properties of the oil, a cumulative deterioration process referred to as ageing. Three mechanistically distinct pathways are identified: thermal ageing, caused by sustained or cyclic heating to elevated temperatures; electrochemical ageing, resulting from the synergistic action of the electric field and reactive chemical species; and electrical ageing, driven by persistent partial discharge activity and ionisation phenomena, which manifests as rising dielectric loss and falling insulation resistance.

I.4.2.2 Role of Transformer Oil

Within the transformer, the insulating oil fulfils three fundamental and interrelated roles:

- Electrical insulation between live conductors and the grounded tank.
- Thermal cooling — dissipating heat generated by winding and core losses toward external radiators.
- Retardation of solid insulation degradation by impregnating the cellulose paper and displacing moisture.

I.5 Categories of Insulating Oils

Dielectric liquids used in power transformers are grouped according to their origin into three distinct families: mineral oils, synthetic oils, and vegetable oils, listed in the order of their historical introduction to transformer service. Table I.3 offers a comparative summary of the critical performance indicators for each fluid category as deployed in oil-immersed transformer applications.

Table I.3 — Performance characteristics of dielectric liquids used in immersed transformers. [2]

Property	Mineral Oil	Silicone Oil	Synthetic	Vegetable Oils	Test Method
Dielectric Strength	30–85	35–60	45–70	82–97	IEC 60156
Relative	2.1–2.5	2.6–2.9	3.0–3.5	3.1–3.3	IEC 60247
Viscosity at 40°C	3–16	35–40	14–29	16–37	ISO 3104
Pour Point (°C)	−30 to −60	−50 to −60	−40 to −50	−19 to −33	ISO 3016
Flash Point (°C)	100–170	300–310	250–270	315–328	ISO 2592
Fire Point (°C)	110–185	340–350	300–310	350–360	ISO 2592
Density at 20°C	0.83–0.89	0.96–1.10	0.90–1.00	0.87–0.92	ISO 3675
Thermal	0.11–0.16	0.15	0.15	0.16–0.17	DCS
Expansion Coeff.	7–9	10	6.5–10	5.5–5.9	ASTM D1903

I.5.1 Vegetable and Bio-based Oils

Biobased vegetable oils have emerged as an intensively researched alternative to mineral oil, propelled by increasingly stringent environmental legislation and the demand for sustainable, fire-safe dielectric fluids. Notable commercial offerings include Biotemp (ABB) and Envirotemp FR3 (Cooper Power Systems). While these fluids offer high dielectric strength and are readily biodegradable, their elevated kinematic viscosity at low temperatures and their susceptibility to oxidative degradation represent persistent technical barriers to large-scale deployment in power transformer service. [5]

I.5.2 Mineral Oils

Mineral transformer oil is a refined petroleum-derived hydrocarbon fluid whose dominance in the insulating liquid market derives from its well-balanced electrical performance, adequate thermal conductivity, chemical compatibility with cellulose-based insulation materials, and low unit cost of approximately 6 USD/L. The principal drawbacks are its inherent flammability — which presents a fire hazard, particularly in indoor installations — and the environmental risk associated with leaks or accidental spills. [3].

I.5.3 Synthetic and Silicone Oils

Synthetic dielectric fluids are selected when conventional mineral oil cannot satisfy demanding performance requirements, most notably a high degree of fire resistance for transformers sited near populated areas, in tunnels, or within buildings. Three chemical families have been commercially deployed: pentaerythritol-based synthetic esters, silicone polymers (polydimethylsiloxane, PDMS), and chlorinated aromatic hydrocarbons (PCBs), the last of which has been globally phased out owing to their proven environmental toxicity and persistence.

Synthetic ester fluids such as Midel 7131 and Envirotemp 200 achieve flash points exceeding 300°C, making them well-suited for fire-retardant distribution transformers. Nevertheless, their unit cost — roughly four times that of mineral oil — and the comparatively limited body of long-term in-service data have constrained their broader adoption. Silicone-based fluids (PDMS) demonstrate outstanding thermal stability up to 150°C and are particularly favoured in traction applications; their drawbacks include a unit cost approximately eight times higher than mineral oil and a non-biodegradable character that complicates waste disposal and end-of-life management. [4]

I.6 Characteristics of Transformer Insulating Oils

Proper specification and acceptance of a transformer insulating oil demand systematic assessment across three distinct property domains: electrical, physical, and chemical. The internationally recognised test standards governing each domain are compiled in Table I.4. [6]

Table I.4 — Transformer oil characteristic test standards.

Test Group	Test Name	Standard
Routine Tests	Colour Determination	ISO 2049
	Breakdown Voltage	IEC 60156
	Water Content	IEC 60814
	Acidity (Neutralisation Number)	IEC 62021
	Dielectric Loss Factor	IEC 60247
	Inhibitor Content	IEC 60666
	Oxidation Stability	IEC 61125 Method C
Additional Tests	Interfacial Tension	ISO 6295
	Particle Count	IEC 60970
	Flash Point	ISO 2719
Special Investigative	Pour Point / Density	ISO 3016 / ISO 3675
	Viscosity	ISO 3104
	Polychlorinated Biphenyls (PCB)	IEC 61619
	Corrosive Sulfur	DIN 51353

I.6.1 Electrical Properties

The electrical behaviour of dielectric liquids is fundamentally determined by their molecular structure and the nature and concentration of any contaminants present. A comprehensive characterisation of these properties draws on knowledge spanning electrochemistry, dielectric physics, and materials science.

I.6.1.1 Conductivity and Resistivity

Electrical conduction in dielectric liquids is attributable to ionic species and other free charge carriers that drift under the action of an applied electric field. Adequate insulation quality requires that conductivity be kept to an absolute minimum, which is equivalent to maximising resistivity. Well-conditioned transformer oils exhibit conductivity in the approximate range of 10^{-11} to 10^{-13} S/m under normal operating conditions.

I.6.1.2 Dielectric Strength and Breakdown Voltage

Dielectric strength E_e represents the limiting electric field intensity at which an insulating liquid undergoes disruptive breakdown. It is formally defined as the quotient of the breakdown voltage U_e and the inter-electrode separation e, as specified in IEC 60156-1995:

$$Ec = Uc / e \qquad \text{(I.1)}$$

This parameter is highly sensitive to electrode shape, gap spacing, moisture content, and the previous thermal and electrical history of the oil sample. Figure 1.3 illustrates the positive temperature dependence of breakdown voltage: as temperature rises, water solubility in oil increases, reducing the population of free water droplets that would otherwise act as breakdown-initiating heterogeneities. Successive breakdown events initially enhance performance by driving out dissolved gas, but cause eventual degradation through progressive oil carbonisation and molecular decomposition. [7]

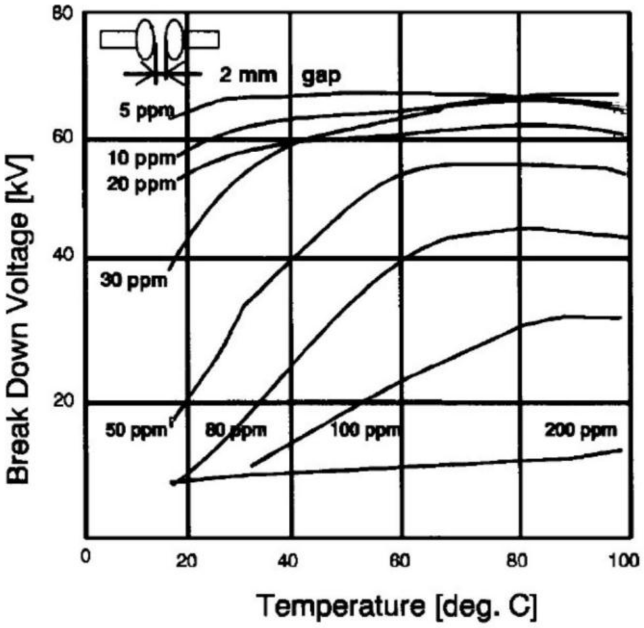

Figure I.3 — Effect of temperature on insulating oil breakdown voltage.

I.6.1.3 Relative Permittivity

Permittivity quantifies the degree to which a dielectric material can be electrically polarised in response to an applied field. The absolute permittivity ε is expressed through its relationship with the permittivity of free space ε_0 = 8.85 pF/m:

$$\varepsilon = \varepsilon_0 \cdot \varepsilon r \qquad \text{(I.2)}$$

In this expression, the relative permittivity εr is defined operationally as the ratio between the capacitance of an electrode assembly immersed in the insulating liquid (C_r) and the capacitance of the same assembly measured in vacuum (C_0):

$$\varepsilon r = Cr / C_0 \qquad \text{(I.3)}$$

For mineral transformer oils, εr lies in the range 2.1–2.5 at a reference temperature of 25°C, as reported in Table I.3.

I.6.1.4 Dielectric Loss Factor (tan δ)

The dissipation factor tanδ quantifies dielectric losses in alternating voltage and is directly related to the oil's resistivity and permittivity. A low tanδ value confirms minimal ionic contamination and high oil purity. Both the dissipation factor and dielectric losses increase with temperature, indicating that high-temperature operation accelerates insulation degradation.

I.6.1.5 Partial Discharges and Gassing

Insulation micro-defects — gas-filled voids, moisture droplets in oil, and conducting particles — concentrate the local electric field until it surpasses the PD inception threshold, triggering repetitive, spatially confined breakdown events without bridging the full insulation gap. The energy dissipated by each discharge decomposes the surrounding oil into a reproducible set of dissolved gases (H_2, CH_4, C_2H_6, C_2H_4, C_2H_2, CO, CO_2), and it is precisely the identification and quantification of this gas mixture that underpins the DGA diagnostic approach. The gassing tendency of an oil — the signed rate at which gas is evolved or absorbed under PD activity at 10 kV and 80°C, in mm^3/min — is a key selection criterion; a negative value, indicating gas absorption, is preferred because it inhibits void enlargement and retards progressive insulation damage. [7]

I.6.2 Physical Properties

I.6.2.1 Flash Point and Fire Point

The flash point (the lowest temperature at which the oil vapour above the liquid surface forms a transiently ignitable mixture with air, per ISO 2719) and the fire point (the temperature at which full, self-sustaining combustion is maintained for at least five seconds) together define the fire risk envelope of the insulating fluid. For mineral oils these values lie in the range 100–170°C, which is relatively low and drives fire protection requirements for indoor installations. Synthetic ester and vegetable oil alternatives achieve substantially higher values (250–328°C), which has been a key driver of their selection in fire-sensitive environments.

I.6.2.2 Thermal Properties

Specific heat capacity *Cp* determines how effectively the oil can store thermal energy during transient overload events and is estimated from the empirical relation:

$$Cp = (1684 - 3.39T) / \rho 15 \qquad (1.4)$$

In this expression T is the absolute temperature in Kelvin and $\rho 15$ the density at the reference temperature of 15°C. The companion quantity, thermal conductivity λ, governs steady-state heat transfer from the winding surfaces to the surrounding oil and typically falls in the range 0.11–0.14 W/(K·m) for mineral oil; as shown in Figure I.4, λ decreases monotonically with rising temperature.

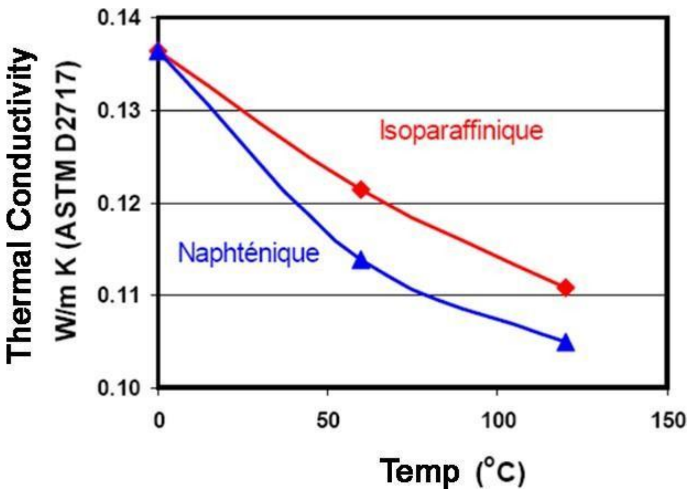

Figure I.4 — Thermal conductivity of insulating oil as a function of temperature.

I.6.2.3 Density, Colour, and Expansion Coefficient

The density of transformer oil at temperature θ is computed from its reference value at 20°C through the linear relation $\rho\theta = \rho 20\cdot(1 - \alpha v[\theta - 20])$, where αv is the volumetric thermal expansion coefficient, which lies between 5×10^{-4} and 10×10^{-4} K^{-1} (ASTM D1903). Visually, high-quality refined oil presents a clear to light-yellow appearance; progressive darkening is an indicative sign of advancing oxidative ageing. A defining requirement for transformer oil quality is that its density must remain below 1000 kg/m³ — less than that of water — so that any emulsified water remains suspended rather than settling to form electrically conductive water layers.

I.6.2.4 Viscosity

Kinematic viscosity directly governs the effectiveness of convective heat transfer within the transformer: oil that is excessively viscous circulates poorly through the cooling circuit, raising winding hot-spot temperatures and accelerating thermal ageing. Viscosity is determined by the molecular weight distribution of the constituent hydrocarbon fractions and is conventionally expressed in centistokes (cSt). The viscosity index — a dimensionless measure of the sensitivity of viscosity to temperature — should be as high as possible to ensure stable thermal performance across the complete range of service temperatures.

I.6.2.5 Pour Point

The pour point, determined according to ISO 3016, is the lowest temperature at which the oil exhibits sufficient mobility to flow under standardised test conditions. For outdoor transformer installations, this parameter must be matched to the coldest anticipated ambient temperature at the installation site; in sub-arctic climates, ambient temperatures as low as −60°C may be encountered, imposing stringent pour point requirements.

I.6.3 Chemical Properties

I.6.3.1 Oxidation Stability

When transformer oil is exposed to dissolved oxygen, it undergoes an autocatalytic free-radical oxidation chain reaction whose rate is strongly promoted by elevated temperature, the presence of moisture, and the catalytic activity of metallic surfaces (copper, iron). The primary oxidation products are soluble acids, aldehydes, and ketones that alter the colour and acidic character of the oil; continued polymerisation of these intermediates yields insoluble resinous sludge. The overall rate of oxygen consumption in this chain reaction is expressed as:

$$\omega = K \cdot [R_0] \cdot [O_2] \qquad (\text{I}.5)$$

Here ω is the rate of oxygen consumption, K the reaction rate constant, $[R_0]$ the concentration of reactive hydrocarbon radicals, and $[O_2]$ the dissolved oxygen concentration. The reaction rate roughly doubles for every 8–10°C increase in temperature above 60°C. The cumulative effects of oxidation include rising viscosity, elevated dielectric losses, enhanced corrosivity toward both cellulose and metallic materials, and ultimately the deposition of sludge that blocks cooling passages and accelerates thermal degradation. Inhibited oil grades incorporate antioxidant additives specifically formulated to interrupt the radical chain and retard these deterioration processes.

I.6.3.2 Acidity

Acidity is expressed as the neutralisation number — the mass of KOH in mg required to neutralise the acidic constituents of one gram of oil — and reflects the accumulation of organic and inorganic acids formed through oil oxidation and atmospheric moisture absorption. Freshly produced oil typically exhibits an acidity of approximately 0.005 mg KOH/g. Once acidity rises appreciably, it attacks the cellulose insulation, corrodes copper and iron surfaces, and promotes sludge precipitation. Quantification is performed by colorimetric titration (ISO 6618) or by potentiometric titration (IEC 62021-1).

I.6.3.3 Water Content

Water content must be minimised throughout the transformer's service life. IEC 60814-1997 defines water content w(μg/g) = m/M, where m is the titrated water mass (μg) and M is the oil mass (g). New oil must contain less than 10 ppm; in-service limits are typically 30 ppm. The water solubility W□ in oil increases with temperature according to W□ = $W_o$il · exp(−B/T), where T is in Kelvin. This temperature-dependence means that water may dissolve at operating temperature but precipitate as free water upon cooling, presenting a latent risk to insulation integrity.

I.7 Ageing of Insulating Oils

Dissolved oxygen and moisture constitute the two dominant ageing agents for transformer insulating oil, and their combined action underpins four interdependent deterioration mechanisms: oxidation, driven by the chemical reaction between the oil and dissolved Oxygen and strongly promoted by heat and metallic catalysts; hydrolysis, caused by water-induced scission of ester bonds and cellulose polymer chains; pyrolysis, occurring through thermal decomposition at overheated locations within the windings; and electrical degradation, associated with the sustained activity of partial discharges. In open-breathing transformer designs — which account for the great majority of units in operational service — the conservator and silica-gel breather offer only partial protection against atmospheric oxygen and water vapour ingress, rendering these units particularly vulnerable to oxidative and hydrolytic ageing pathways.

I.7.1 Effects of Humidity

Of all the degradants encountered in transformer service, moisture is widely regarded as the most injurious to electrical insulation. Water enters the system through two principal pathways: atmospheric ingress through the conservator breather in open-breathing designs, and the thermally driven release of water from the cellulose insulation, which retains a residual moisture of at least 0.2% by mass even after thorough vacuum-drying. Within the oil, water may be present in dissolved form, as dispersed microscopic droplets, or as an emulsion. Even small quantities of dissolved water cause a sharp reduction in breakdown voltage, while the precipitation of free water droplets upon cooling — a consequence of the inverse relationship between water solubility and temperature — presents an acute and immediate risk to insulation integrity. For this reason, the relative water saturation at the test temperature must always be reported alongside the absolute water content figure to provide a fully meaningful characterisation.

I.7.2 Thermal Effects

Sustained partial discharge activity decomposes the surrounding oil and erodes the adjacent solid insulation through a combination of chemical attack, ionisation bombardment, and localised thermal effects, generating dissolved gases and carbonaceous deposits that, over time, create preferential conductive pathways culminating in catastrophic dielectric breakdown. Temperature, although not in itself a primary ageing agent, functions as a powerful accelerant for all other degradation pathways: the rates of oxidation, hydrolysis, and pyrolysis all exhibit a pronounced exponential dependence on temperature. Within transformer windings, localised hot spots arising from eddy current concentration, loose or corroded electrical contacts, or cooling system malfunction can attain temperatures exceeding 500°C, generating specific fault signature gases that are detectable and interpretable through dissolved gas analysis. [8]

I.7.3 Oxidation Mechanisms

Oxidative degradation of mineral oil is thermally initiated and sustained by the reaction of hydrocarbon radicals with dissolved molecular oxygen, with transformer construction materials — copper windings, iron core laminations, and cellulosic paper insulation — acting as both homogeneous and heterogeneous catalytic agents. The process is autocatalytic: the initial free-radical chain produces soluble primary products (aldehydes, ketones, carboxylic acids) that discolour the oil and increase its acidity, while subsequent polymerisation of these intermediates generates insoluble sludge. Sludge deposition on winding surfaces and in cooling passages progressively impairs heat dissipation, raises winding temperatures, and reduces the dielectric performance of the oil. [9]

I.8 Diagnosis of Transformer Oil by Dissolved Gas Analysis

I.8.1 Dissolved Gas Analysis (DGA)

Dissolved gas analysis has been in industrial use for more than four decades and is governed by the international standards IEC 60599 and IEEE C57.104. It is universally recognised as the most dependable non-destructive diagnostic method for oil-filled power transformers in operational service. DGA requires only a modest volume of oil sampled from the transformer, imposes no interruption to service, and can be executed in a certified laboratory or directly at the substation using portable instruments. The seven key indicator gases monitored are hydrogen (H2), methane (CH4), ethane (C2H6), ethylene (C2H4), acetylene (C2H2), carbon monoxide (CO), and carbon dioxide (CO2) , each of which — individually or in combination — is diagnostic of a particular fault type and energy level.

I.8.2 Oil Decomposition and Gas Generation

Regardless of whether a fault is electrical or thermal in nature, its occurrence within the transformer inevitably results in the decomposition of the insulating oil, the solid cellulosic insulation, or both, liberating gas molecules that dissolve in the surrounding oil. The concentrations and mutual proportions of these dissolved gases define a characteristic chemical signature that is specific to the nature, energy level, and probable location of the fault. Tracking the rate of gas generation over successive sampling intervals provides an early warning of fault inception and allows estimation of the transformer’s remaining serviceable life.

I.9 Classification of Power Transformer Faults

Under the frameworks established by IEC 60599-2008 and IEEE C57.104-2019, transformer defects identifiable through DGA are organised into two primary categories

ذذ— faults of electrical origin and faults of thermal origin — each further divided into subtypes according to the energy magnitude and temperature range involved, yielding six recognised fault classes: [10]

- Partial discharges (PD) — low-energy localised electrical discharges in voids, bubbles, or near sharp edges.
- Low-energy electrical discharges (D1) — sparking faults of limited spatial extent.
- High-energy electrical discharges (D2) — sustained arcing with substantial energy release.
- Thermal fault T1 — localised overheating below 300°C.
- Thermal fault T2 — overheating in the range 300°C to 700°C.
- Thermal fault T3 — severe overheating above 700°C.

I 9.1 Thermal Faults

زThermal faults in power transformers originate from a variety of sources, including conductor overheating, short-circuit events, eddy-current-induced winding losses, poor electrical connections, and inadequate cooling arrangements. When overheating is confined to a particular region rather than distributed uniformly, it gives rise to what is commonly referred to as a hot spot. Surface temperatures at such localized points can climb as high as 1500°C, generating intense local heat that acts upon the surrounding insulating oil and triggers the decomposition of hydrocarbon molecules into gaseous byproducts. The composition and relative proportions of these dissolved fault gases are not arbitrary — each gas or gas mixture is associated with a characteristic temperature range at which it preferentially forms. This temperature-dependent nature of gas generation makes dissolved gas analysis a reliable diagnostic tool for identifying the thermal severity and likely origin of developing faults within the transformer.

I.9.2 Partial Discharges

Partial discharges are localized, low-energy electrical breakdown events that occur within a confined region of the insulation without bridging the full dielectric gap. They originate at internal voids, entrapped gas pockets, moisture droplets, and geometric field enhancements such as sharp conductor edges, where local electric stress exceeds the dielectric withstand threshold. Their principal decomposition products are hydrogen and methane, reflecting the relatively low energy density characteristic of this fault type.

Among all degradation mechanisms affecting solid cellulosic insulation, partial discharge activity is the most destructive, progressively eroding the fibre structure through repeated electrical, chemical, and thermal stress until complete insulation failure occurs. Continuous or periodic monitoring is therefore essential for early fault detection and timely maintenance intervention.

I.9.3 Electrical Discharges (Arcing)

When a full arc bridges the inter-electrode gap, the resulting D2 fault liberates large quantities of C_2H_2 and H_2 at local plasma temperatures above 5000°C; the accompanying rapid pressure surge creates an immediate explosion hazard that demands the earliest possible fault detection. Although D1 sparking faults release comparatively modest gas volumes, their diagnostic weight is no less significant — they are well-established precursors that frequently precede the onset of the far more destructive D2 arcing regime if left unaddressed."

I.10 Conclusion

This chapter has presented a comprehensive overview of insulating oils for power transformers, covering transformer classification, insulation systems, oil categories, physicochemical properties, ageing mechanisms, and the DGA diagnostic framework. The following principal conclusions are drawn.

The selection of a transformer insulating oil cannot be based solely on electrical, physical, or chemical properties considered in isolation: ageing resistance, thermal management capability, fire safety, and environmental compliance must all be evaluated jointly. Among the available fluid types, mineral oil remains the preferred choice for the vast majority of applications due to its well-characterised properties and low cost, despite its flammability and susceptibility to oxidation. Synthetic esters and vegetable oils offer compelling advantages in fire-sensitive and environmentally sensitive installations but at higher cost and with less accumulated service experience.

Oxygen, elevated temperature, and moisture are the dominant ageing agents for insulating oil, acting synergistically through oxidation, pyrolysis, and hydrolysis mechanisms. DGA is established as the most reliable non-destructive technique for the in-service assessment of transformer condition, providing a direct chemical fingerprint of active fault mechanisms. The interpretation of DGA results by standardised methods — IEEE C57.104, IEC 60599, Rogers ratios, and the Duval Triangle — forms the diagnostic foundation that motivates the AI-based fault classification approach developed in the subsequent chapters of this work.

Chapter II

Methods for detecting faults in electrical transformer oils

II.1 Introduction

Transformer oil constitutes a continuous chemical record of all thermal and electrical events occurring within the equipment. Every internal fault — whether of thermal or electrical origin — decomposes the insulating oil or the solid cellulose insulation, releasing characteristic gas species that dissolve in the oil and can be precisely measured by gas chromatography. Complementary physicochemical parameters — viscosity, acidity, interfacial tension, and dielectric strength — further characterise the insulation condition, contamination level, and remaining service life.

Reliable and timely fault detection is critical for power system integrity: undiagnosed incipient faults may escalate into catastrophic transformer failure, causing extended outages and significant economic losses, whereas false alarms drive unnecessary shutdowns and maintenance costs. This chapter reviews the principal diagnostic methods structured into two categories: (i) traditional physicochemical and dissolved gas analysis (DGA) techniques founded on established standards, and (ii) advanced artificial intelligence (AI)-based approaches that overcome the inherent limitations of conventional methods through data-driven learning.

II.2 Traditional Diagnostic Methods

Conventional diagnostic techniques, refined over several decades of industrial practice, remain the cornerstone of transformer condition monitoring programmes worldwide. They are broadly divided into physicochemical analysis — which evaluates the chemical and physical integrity of the oil — and dissolved gas analysis (DGA) — which identifies gases generated by insulation degradation. Both are complementary and are typically applied in combination to obtain a comprehensive and reliable diagnostic picture.

II.2.1 Physicochemical Tests

Physicochemical tests characterise both the ageing state and the contamination level of the insulating oil, providing an integrated assessment of its dielectric and thermal performance. The parameters described below correspond to those standardised and routinely monitored by SONELGAZ, the Algerian national electricity and gas utility, in its transformer maintenance programme. Table II.1 summarises the test types and applicable standards adopted by SONELGAZ for the analysis of BORAK 22 transformer oil.

Table II.1 — Standards used by SONELGAZ for the analysis of BORAK 22 transformer oil.

Type of Test	Standard
Colour	ASTM D 1500
Kinematic Viscosity	NF-T-60 100
Total Acidity	IEC 296
Dielectric Strength (Rigidity)	IEC 156
Dielectric Losses (tan δ)	IEC 250
Water Content	ISO R 760

A) Water Content

Dissolved moisture is the primary threat to high-voltage insulation. Pre-filling treatment must reduce water content below 10 ppm; the in-service acceptance limit is 30 ppm (ISO R760 / ASTM D1533). Above this threshold, dielectric strength degrades markedly and cellulose ageing accelerates. Relative water saturation, which varies with temperature and oil acidity, is a more sensitive indicator than absolute concentration. [11]

Figure II.1 — Water content measurement device (Karl Fischer titration unit).

B) Acidity and Neutralisation Number

The neutralisation number (mg KOH/g) quantifies organic acids formed by oil oxidation. New oil presents approximately 0.005 mg KOH/g; IEC 296 sets the in-service limit at 0.03 mg KOH/g. Regeneration is recommended at 0.2 mg KOH/g, as sludge formation initiates near 0.4 mg KOH/g. Measurement is by calorimetric or potentiometric titration. [11]

C) Kinematic Viscosity

Viscosity governs oil circulation and heat dissipation. Elevated viscosity — common in cold climates — impedes flow through cooling channels, raising hot-spot temperatures. It is measured by capillary viscometry and is governed by the molecular weight distribution of the hydrocarbon fractions. [12]

Figure II.2 — Kinematic viscosity measurement device (capillary viscometer).

D) Breakdown Voltage (Dielectric Strength)

Dielectric strength is the maximum voltage the oil sustains before electrical breakdown, and is directly sensitive to moisture and particulate contamination. Tests follow ASTM D877 (sphere electrodes) and ASTM D1816 (VDE electrodes). A declining value is a reliable early warning of oil deterioration or moisture ingress. [11]

Figure II.3 — Breakdown voltage test bench (dielectric strength measurement, ASTM D877).

E) Visual Inspection and Colour

Oil colour, assessed under transmitted light against a standardised scale, provides a rapid qualitative indicator: new oil is clear to pale yellow; darkening toward reddish-brown indicates progressive ageing. Turbidity signals free water, insoluble sludge, carbon particles from arcing, or fibrous contamination, and should prompt immediate full investigation. [13]

Figure II.4 — Oil samples at progressive degradation stages (laboratory analysis).

F) Dielectric Dissipation Factor (tan δ)

The dissipation factor quantifies polar ionic contaminants and charge carriers that degrade the oil's insulating function. Measured at ambient temperature and at 90 °C (IEC 60247), a low tan δ confirms oil purity; a rising value indicates contamination or accelerated degradation, warranting prompt investigation. [13]

G) Interfacial Tension (IFT)

IFT measures the force per unit length at the oil–water interface and is highly sensitive to trace polar oxidation products (acids, aldehydes, peroxides) that reduce the value below the 40 mN/m typical of new oil. Measured per ASTM D971, IFT detects degradation at concentrations undetectable by other methods. [14]

Figure II.5 — Interfacial tension measurement device (ring method, ASTM D971).

H) Myers Index and Inhibitor Content

The Myers Index (IFT / TAN) integrates two complementary ageing indicators; a value below 100 signals advanced oxidation and the need for near-term replacement. Inhibited oils contain synthetic antioxidants that intercept free-radical intermediates; once depleted, oxidation accelerates sharply. Inhibitor content is monitored by UV spectrophotometry or HPLC and must be replenished before depletion to maintain reliability. [15]

II.2.2 Dissolved Gas Analysis (DGA)

Dissolved gas analysis is universally recognised as the most informative and cost-effective diagnostic technique for in-service power transformers. Every thermal or electrical fault decomposes the insulating oil and/or solid cellulose insulation, generating characteristic gas species whose nature, absolute concentration, and mutual ratios constitute a unique chemical fingerprint enabling identification of the fault type, its probable location, and its relative severity. DGA methods range in sophistication from simple individual gas threshold monitoring to multi-ratio coding schemes and continuous graphical approaches.

II.2.2.1 Individual Gas Method

Specific gases — or gas combinations — are associated with particular fault mechanisms. Combustible gases include H_2, CH_4, C_2H_6, C_2H_4, C_2H_2, and CO; non-combustible gases include CO_2, N_2, and O_2. Table II.2 summarises these associations. Despite its simplicity, the individual gas method has a low fault-classification rate and should be used only as a preliminary screening tool[16].

Table II.2 — Dissolved gases and associated transformer fault types.

Gas	Associated Fault
Acetylene (C_2H_2)	High-energy electrical fault (arcs, sparks)
Ethylene (C_2H_4)	Thermal fault — oil overheating or thermal decomposition
Ethane (C_2H_6)	Low-energy thermal fault; oil thermal decomposition
Hydrogen (H_2)	Low-energy electrical fault (corona, partial discharges)
Methane (CH_4)	Partial discharges or oil thermal decomposition
Carbon monoxide	Thermal decomposition of cellulose insulation
Carbon dioxide (CO_2)	Thermal decomposition of cellulose insulation
Nitrogen (N_2)	Sample collection defect
Oxygen (O_2)	Oil leakage or inadequate sealing

II.2.2.2 IEEE C57.104 — Total Dissolved Gas Concentration (TDGC)

IEEE C57.104-2019 cumulates the ppm concentrations of all combustible gases (H_2, CH_4, C_2H_2, C_2H_4, C_2H_6, CO, CO_2) and defines four health conditions (Table II.2). Condition 1 is normal; Condition 2 requires increased sampling frequency; Condition 3 mandates daily sampling and investigation; Condition 4 necessitates immediate shutdown. [17]

Table II.*3 — Dissolved gas thresholds per IEEE C57.104-2019 (µg/L, ppm).*

Condition	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6	CO	CO_2	TDGC
1 — Normal	≤100	≤120	≤1	≤50	≤65	≤350	≤2500	≤720
2 — Caution	101–	121–	2–9	51–100	66–100	351–	2501–	721–
3 — High	701–	401–	10–	101–	101–	571–	4001–	1921–
4 — Critical	>1800	>1000	>35	>200	>150	>1400	>10000	>4630

II.2.2.3 Key Gas Method (KGM)

KGM identifies fault type from the dominant gas species rather than absolute concentrations (Table II.3). Although intuitive, it cannot reliably resolve overlapping faults and is recommended only as a preliminary screening step alongside more discriminating methods. [18]

Table II.4 — Fault classification criteria of the Key Gas Method.

Key Gas	Fault Type	Characteristic Gases	Dominant %
C_2H_4	Oil Overheating	C_2H_4 and CH_4 dominate; traces of	C_2H_4: 63%;
CO	Cellulose	Large CO and CO_2; CH_4 and C_2H_4 if	CO: 92%
H_2	Partial	H_2 and CH_4 dominate; CO/CO_2 if	H_2: 85%; CH_4:
H_2+C_2H_2	Electrical	Significant H_2 and C_2H_2; CO/CO_2 if	H_2: 60%; C_2H_2:

II.2.3 Gas Concentration Ratio Methods

Gas concentration ratio methods compare pairs of combustible gases rather than evaluating absolute concentrations, thereby reducing sensitivity to variations in oil sampling volume, dissolved gas extraction efficiency, and instrument calibration. Six ratios are standardised: R1=CH_4/H_2, R2=C_2H_2/C_2H_4, R3=C_2H_2/CH_4, R4=C_2H_6/C_2H_2, R5=C_2H_4/C_2H_6, R6=C_2H_6/CH_4. First introduced by Dornenburg and refined by Rogers and the IEC, three widely adopted standards employing subsets of these ratios are described below. [5, 16]

II.2.3.1 Dornenburg Ratio Method (DRM)

The DRM is applicable only when each key gas exceeds its minimum threshold L1 (Table II.4). Ratios R1–R4 then classify the fault into one of three categories (Table II.5). Its primary limitation is applicability only at elevated gas concentrations, restricting early-stage detection.

Table II.5 — Minimum gas concentration thresholds (L1) for DRM application[17]

Gas	L1 Threshold (ppm)
H_2	100
CH_4	120
CO	350
C_2H_2	35
C_2H_4	50
C_2H_6	65

Table II.6 — Fault classification criteria in the Dornenburg Ratio Method.

Fault Type	R1	R2	R3	R4
Thermal Decomposition	>1	<0.75	<0.3	>0.4
Partial Discharge (Low-	<0.1	Not	<0.3	>0.4
Electrical Arcing (High-	0.1–1	>0.75	>0.3	<0.4

II.2.3.2 Rogers Ratio Method (RRM)

The RRM eliminates the L1 prerequisite, enabling early-stage application. Each of the three ratios (R1, R2, R5) is assigned a code 0, 1, or 2 per Table 2.6; the resulting triple-code combination maps to one of nine fault diagnoses (Table II.7). A key limitation is incomplete coverage: only 9 of 27 code combinations are interpretable. [19]

Table II.7 — Gas ratio ranges and codes in the Rogers method.

Gas Ratio	Value Range	Code
R1 = CH_4/H_2	< 0.1	1
	$0.1 \leq R1 \leq 1$	0
	> 1	2
R2 = C_2H_2/C_2H_4	< 0.1	0
	$0.1 \leq R2 \leq 3$	1
	> 3	2
R5 = C_2H_4/C_2H_6	< 1	0
	$1 \leq R5 \leq 3$	1
	> 3	2

Table II.8 — Code combinations and fault diagnoses in the Rogers method.

R1	R2	R5	Fault Diagnosis
0	0	0	Normal operation — no fault detected
1	0	0	Partial discharges — low energy
1	1	0	Partial discharges — high energy
0	1–2	1–2	Electrical discharge — low energy
0	1	2	Electrical discharge — high energy
0	0	1	Thermal fault — T < 150 °C
2	0	0	Thermal fault — 150 °C < T < 300 °C
2	0	1	Thermal fault — 300 °C < T < 700 °C
2	0	2	Thermal fault — T > 700 °C

II.2.3.3 IEC 60599 Method

IEC 60599 adopts the Rogers ratios and coding scheme but standardises six fault categories: PD, D1, D2, T1 (T<300°C), T2 (300°C<T<700°C), and T3 (T>700°C), per Table II.8. As with Rogers, only 9 of 27 combinations are interpretable. The standard explicitly recommends combining DGA with service history and other diagnostic data. [6]

Table II.9 — IEC 60599 diagnostic criteria (NS = Not Significant).

Code	Fault Type	R1	R2	R5
PD	Partial discharges	NS	< 0.1	< 0.2
D1	Low-energy discharge	> 1	0.1–0.5	> 1
D2	High-energy discharge	0.6–2.5	0.1–1	> 2
T1	Thermal fault (T < 300	NS	> 0.1	< 1
T2	Thermal fault (300–	< 0.1	> 1	1–4
T3	Thermal fault (T > 700	≥0.2	> 1	> 4

II.2.4 Graphical Methods — Duval Triangle

The Duval Triangle plots three-gas percentage contributions as a point within a zoned equilateral triangle, providing a continuous visual mapping of fault types. Seven versions address different oil types (Table II.9); Triangles 1, 2, 4, and 5 apply to mineral oils. The method is more tolerant of borderline cases than fixed-threshold ratio approaches and is widely recommended as a complement to ratio-based methods.

Table II.10 — Gas combinations used in each Duval Triangle version.

Triangle	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6
1 — mineral oil		✓	✓	✓	
2 — mineral oil (stray		✓	✓	✓	
4 — mineral oil	✓	✓		✓	
5 — mineral oil (PD		✓	✓	✓	
3, 6, 7 —	var.	var.	var.	var.	var.

Procedure: (1) compute each gas as a percentage of the three-gas sum; (2) project values onto the triangle axes; (3) locate the centroid; (4) identify the fault zone containing the centroid. The approach captures intermediate fault states more naturally than threshold-based ratio methods, and its visual nature aids interpretation by non-specialist engineers.

II.3 Advanced Methods: Artificial Intelligence-Based Diagnosis

Despite their widespread adoption, conventional DGA methods suffer from incomplete fault coverage, threshold dependencies, and inability to resolve overlapping fault types. Artificial intelligence (AI)-based methods address these limitations through data-driven learning from historical DGA records, offering adaptive and comprehensive diagnostic capabilities without relying on predefined threshold rules or ratio boundaries.

II.3.1 Overview of Artificial Intelligence

Artificial intelligence (AI), formally established as a discipline in 1956, enables machines to simulate human cognitive functions including reasoning, learning, and adaptation. Within the AI hierarchy, machine learning (ML) uses statistical algorithms to learn from data, while deep learning (DL) extends ML through multi-layer neural architectures that automatically extract hierarchical features. This relationship is illustrated in Figure II.6. [20]

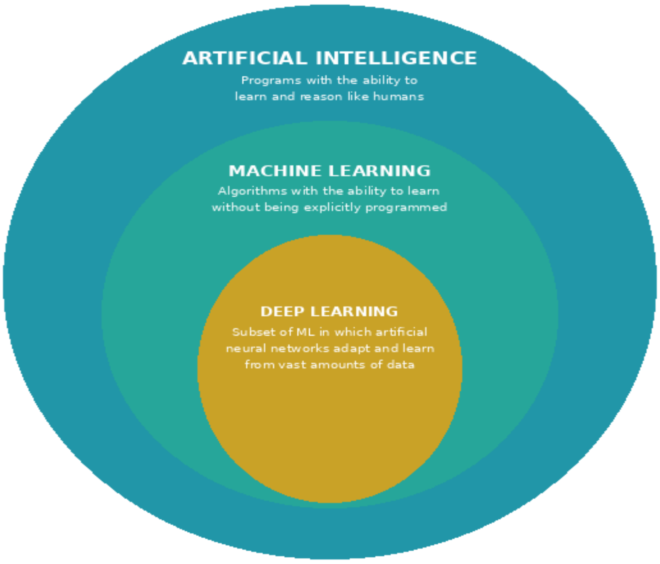

Figure II.6 — Hierarchical relationship between Artificial Intelligence, Machine Learning, and Deep Learning.

The adoption of AI in transformer diagnostics has been driven by the growing availability of large DGA datasets, advances in computational hardware, and the demonstrated inability of conventional methods to achieve satisfactory multi-class classification accuracy.

II.3.2 Machine Learning

Machine learning develops algorithms that extract patterns and relationships directly from data without explicit task-specific programming. A standard ML workflow requires two separate datasets: a training set used to optimise model parameters by minimising a defined loss function, and a test set reserved for unbiased evaluation of generalisation performance on unseen data. ML algorithms are broadly divided into two categories according to the nature of their training signal (Figure II.7):

- Supervised learning: The model trains on labelled input–output pairs to learn a mapping Y=f(X), covering classification (discrete labels) and regression (continuous values).
- Unsupervised learning: Applied to unlabelled data to discover latent structure through clustering (k-Means, FCM) or association algorithms.

Transformer fault diagnosis is a multi-class supervised classification problem: given a DGA feature vector, the model assigns the condition to one of the standardised fault classes (PD, D1, D2, T1, T2, T3).

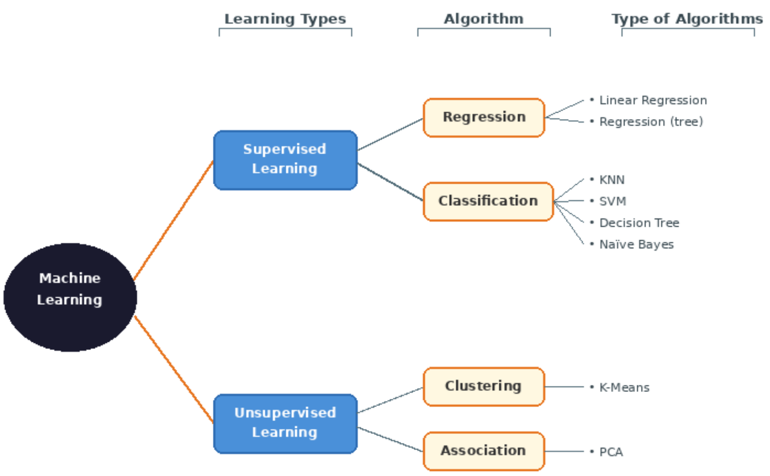

Figure II.7 — Machine learning taxonomy: supervised (regression, classification) and unsupervised (clustering, association) branches. [21]

II.3.3 Supervised Classification Algorithms

The supervised classification algorithms reviewed below represent those most frequently applied to transformer DGA fault diagnosis in the peer-reviewed literature. Each embodies distinct assumptions about the structure of the decision boundary separating fault classes, and each presents characteristic trade-offs between classification accuracy, model interpretability, and computational cost — factors that must be carefully weighed against the properties of the available DGA dataset.

II.3.3.1 Support Vector Machine (SVM)

Introduced by Cortes and Vapnik (1995), SVMs seek an optimal separating hyperplane in feature space that maximises the geometric margin between the nearest training examples of each class — the support vectors. When the data are not linearly separable, the kernel trick implicitly maps the inputs into a higher-dimensional space where linear separation becomes feasible. In transformer fault diagnosis, standalone SVM performance is constrained by the complexity and non-linearity of DGA data; hybrid approaches integrating SVM with GA-based feature screening (GA-SVM-FS), Modified Evolutionary PSO (MEPSO), and the Gray Wolf Optimizer have achieved classification accuracy improvements of 3–30% over standard gas-ratio feature sets.

Strengths: Strong statistical learning foundation; effective in high-dimensional spaces; memory-efficient.

Limitations: Poor scalability to large datasets; sensitive to kernel and regularisation parameter selection.

II.3.3.2 K-Nearest Neighbors (KNN)

KNN classifies a new sample by majority vote among its K nearest training instances, with proximity measured by Euclidean, Manhattan, or Minkowski distance. The algorithm requires no explicit training phase; however, the choice of K critically determines classification quality — small K values cause overfitting to noise, while large values introduce bias toward dominant classes. In transformer fault diagnosis, combined KNN–k-Means approaches achieve 93% accuracy for DGA cases unresolvable by the Duval Triangle, though performance degrades markedly in the presence of irrelevant or redundant features (curse of dimensionality). [22]

Strengths: Simple implementation; multi-class capable; robust to label noise.

Limitations: High inference cost; memory-intensive; sensitive to feature relevance and choice of K.

II.3.3.3 Random Forest (RF)

Random Forests (Breiman, 2001), building on Ho's 1995 random subspace method, construct an ensemble of decision trees each trained on a distinct bootstrap sample of the training data, with a randomly selected feature subset evaluated at each node split. This dual randomisation — in data sampling and feature selection — substantially reduces prediction variance and the overfitting tendency of individual trees. Random Forests provide built-in feature importance estimation without additional preprocessing and consistently outperform single decision trees across high-dimensional DGA feature sets (Figure II.8).

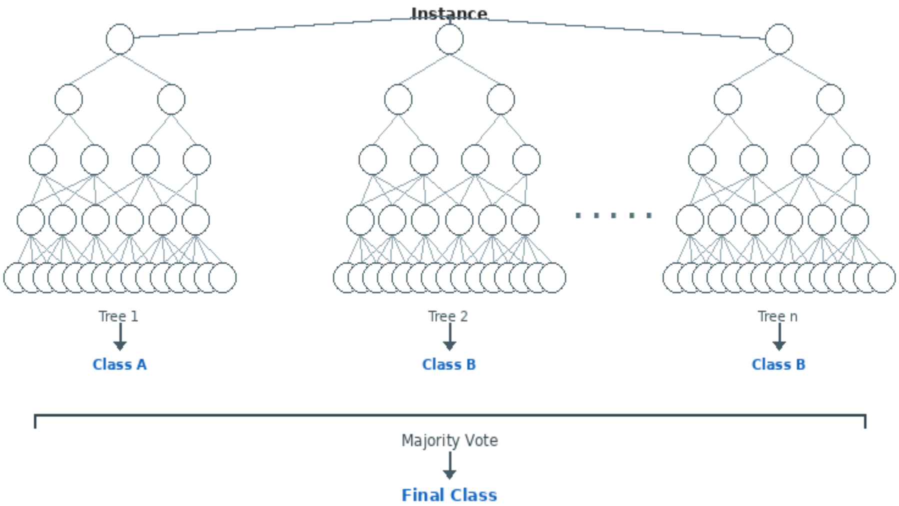

Figure II.8 — Principle of the Random Forest: ensemble of n decision trees with majority voting.

Strengths: Effective overfitting prevention; built-in feature importance; parallelisable training.

Limitations: Reduced interpretability ('black box'); high memory consumption for large forests.

II.3.3.4 Clustering Algorithms

The Fuzzy C-Means (FCM) algorithm, enhanced with exponential similarity functions and modified membership update rules, eliminates local extrema in the objective function and improves DGA fault classification accuracy compared to standard k-Means. Self-Organising Maps (SOM) project high-dimensional DGA data onto a lower-dimensional grid while preserving inter-sample topological relationships; SOM classifiers have demonstrated accuracy exceeding SVM with only 60% of available labelled training data. Advanced hybrid Kernel FCM (KFCM) combined with Kernel Principal Component Analysis (KPCA) enables real-time anomaly detection by comparing kernel-space projections of current and historical DGA measurements against dynamically adjusted thresholds that track changing operating conditions.

II.3.4 Deep Learning

Deep learning (Hinton et al., 2006) extends classical neural networks by stacking multiple nonlinear transformation layers, each learning progressively more abstract feature representations from the layer below. This hierarchical extraction capability fundamentally distinguishes deep architectures from shallow ML models that depend on manually engineered features. For transformer diagnostics, the principal advantages are: automatic feature extraction directly from raw gas concentrations; superior scalability to large DGA datasets; adaptability across diverse fault types; and accuracy that improves monotonically with training data volume.

II.3.4.1 Artificial Neural Networks (ANN)

Artificial Neural Networks, first formalised by McCulloch and Pitts (1943), consist of interconnected processing units (neurons) organised in successive layers. Each neuron computes $Z=\Sigma\omega_i x_i$ and applies $Y=f(Z+\theta)$, where θ is the bias threshold. Two architecture families are distinguished: feedforward networks (SLP, MLP, RBF) for static input-output mapping, and recurrent networks (LSTM, Hopfield, ART, SOM) for temporal sequence modelling. Table II.10 summarises the biological-to-artificial neuron analogy that motivates the ANN computational model.

Table II.11 — Biological-to-artificial neuron analogy.

Biological Neuron	Artificial Neuron	Symbol
Soma (cell body)	Neuron node	—
Dendrites	Inputs	x_i, X
Axon	Output	Y
Synapse	Weights	W_i

II.3.4.2 Activation Functions and Network Architectures

Activation functions — including threshold (Hardlim, Hardlims), linear (Purelin, Satlin), sigmoid (Logsig), hyperbolic tangent (Tansig), and competitive (Compet) variants — introduce the nonlinearity essential for learning complex, multi-class decision boundaries from DGA feature vectors. The logistic sigmoid and hyperbolic tangent functions are the most widely used in hidden layers, with Tansig typically offering faster convergence due to its zero-centred output range. The feedforward MLP, trained by the backpropagation algorithm with gradient descent, is the architecture adopted in this work (Figure II.9), selected for its established performance in nonlinear multi-class classification and its full compatibility with the available annotated DGA dataset.

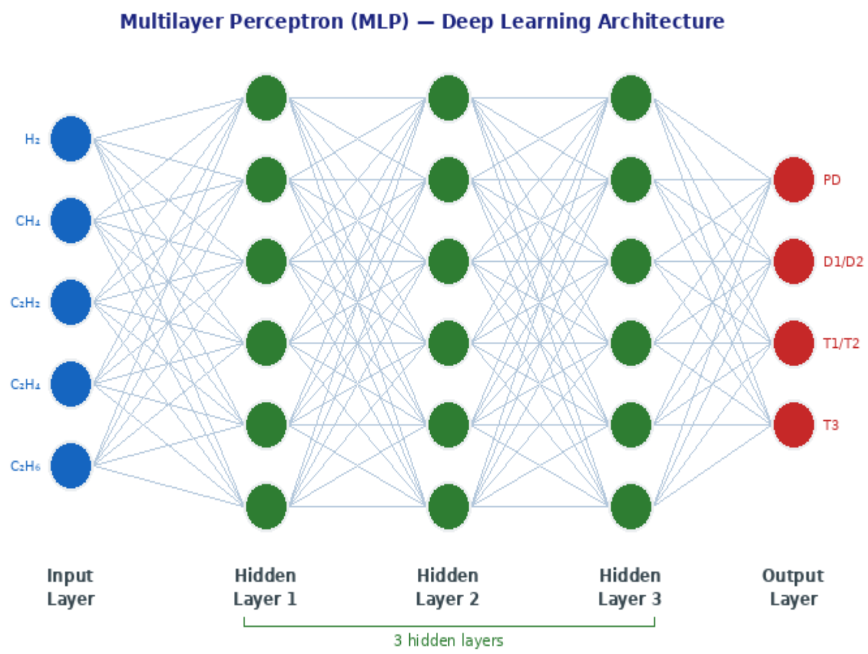

Figure II.9 — MLP architecture for DGA fault classification: input layer (H_2, CH_4, C_2H_2, C_2H_4, C_2H_6), three hidden layers, output layer (PD, D1/D2, T1/T2, T3).

II.3.4.3 Deep Learning Applications in Transformer Diagnosis

DBNs (stacked RBMs with supervised fine-tuning) consistently outperform BP networks and KNN classifiers when integrated with expert-system rules and DGA ratio features. 1D-CNNs combined with SMOTE oversampling exceed 92% accuracy on mixed feature sets; the SDAE-LSTM hybrid and the deep recursive confidence network with adaptive delay achieve accuracy above 95.16% on time-series DGA data.

II.4 Conclusion

This chapter reviewed the principal methods for transformer oil fault detection and classification. Traditional techniques — physicochemical tests (water content, acidity, viscosity, dielectric strength, tanδ, IFT, Myers index, inhibitor content) and DGA methods (TDGC, KGM, Dornenburg, Rogers, IEC 60599, Duval Triangle) — provide well-standardised diagnostic tools but are constrained by incomplete fault coverage and threshold dependencies. AI-based methods, including supervised classifiers (SVM, KNN, RF) and deep learning architectures (MLP, CNN, DBN, LSTM), overcome these limitations through data-driven learning. The feedforward MLP architecture selected for this work offers proven nonlinear multi-class classification performance and compatibility with the available DGA dataset; subsequent chapters detail its design, training, and evaluation.

Chapter III

EXPERIMENTAL STUDY AND AI-BASED DIAGNOSTIC SYSTEM FOR TRANSFORMER OIL AGING

III.1 Introduction

The reliable operation of power transformers is critical to the stability and continuity of electrical networks. Among the key elements ensuring transformer integrity, insulating oil plays a dual role: providing electrical insulation between high-voltage components and facilitating thermal dissipation during operation. As transformers age and undergo repeated electrical stress, the physicochemicaùl properties of insulating oil degrade progressively, ultimately compromising the dielectric performance and operational safety of the equipment.

Conventional diagnostic approaches — such as dissolved gas analysis (DGA), acidity measurement, and moisture content testing — remain the industry standard for assessing oil condition. However, these methods are inherently time-consuming, require specialized laboratory infrastructure, and involve physical sampling from energized equipment, posing logistical and safety challenges in field environments.

This chapter presents a comprehensive experimental and computational study aimed at developing a rapid, non-destructive diagnostic system for transformer oil aging assessment. The study is structured around two complementary objectives: first, the systematic characterization of insulating oil degradation through standardized electrical breakdown testing in accordance with IEC 60156, using two commercially representative oils — Borak 22 and Nynas — across multiple aging states (new, in-service, and out-of-service); and second, the design and validation of an artificial intelligence-based diagnostic framework that leverages computer vision and machine learning to classify oil type, assess operational condition, and estimate the extent of electrical stress from photographic images of oil samples.

By integrating experimental rigor with data-driven modeling, this work contributes to the growing body of research on intelligent condition monitoring, offering a practical and cost-effective alternative to conventional laboratory testing for preliminary screening of transformer oil health.

III.2 Experimental Equipment and Setup

III.2.1 Control Panel

The control panel (Figure III.1) represents a fundamental component of the experimental system, serving as the main interface for supervising and managing the entire testing setup. It incorporates various measuring, protection, and switching control instruments including:

- Digital voltmeter and ammeter
- Circuit breaker and alarm system
- Protection devices for operator safety
- Real-time parameter monitoring displays

The panel ensures accurate monitoring of electrical parameters during testing while maintaining optimal safety conditions for both the system and operators.

Figure III.1 — High voltage control panel used for breakdown voltage testing

III.2.2 Circuit Breaker

A circuit breaker is an automatic electrical protection device designed to ensure safety and reliability by protecting against abnormal operating conditions such as overloads and short circuits. The circuit breaker**:**

- Detects abnormal current variations
- Automatically interrupts power when faults are detected
- Isolates faulty sections to prevent damage propagation
- Maintains overall system stability and reliability

III.2.3 High Voltage Transformer

Specifications: - Type: Single-phase core-type transformer - Rated power: 15 kVA - Frequency: 50 Hz - Primary voltage: 400 V - Secondary voltage: Up to 100 kV - Cooling: Oil-cooled system - Windings: Copper

The transformer generates the high voltage required for breakdown testing under optimal conditions of safety, accuracy, and performance.

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Figure III.2 — High Voltage Transformer 15 kVA high voltage test transformer

III.2.4 Test Cell and Electrodes

Breakdown voltage measurements were performed using sphere-gap electrodes configured according to IEC 60156 standards:

- Electrode geometry: Spherical (Figure III.3)
- Gap distance: 2.5 mm
- Material: Brass
- Test cell: Glass container with capacity for 500 ml oil sample

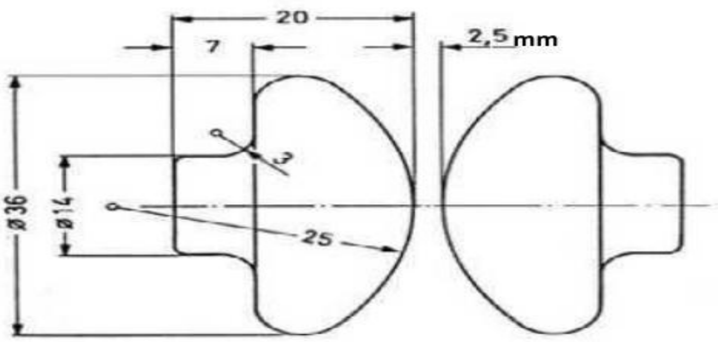


Figure III.3 — Breakdown voltage measurement electrode configuration (IEC 60156)

III.2.5 Complete Test Circuit

The experimental circuit (Figures III.4 and III.5) consists of the following components

Table III.1 — Circuit equipment specifications

Component	Model	Quantity
Test Transformer HT	HV9105	1
Control Panel	HV9103	1
Measurement Capacitor	HV9141	1
AC Voltmeter	HV9150	1
Rod Conductor	HV9108	1
Cup Conductor	HV9109	1
Ground Connection	HV9110	1
Test Tank	HV9137	1

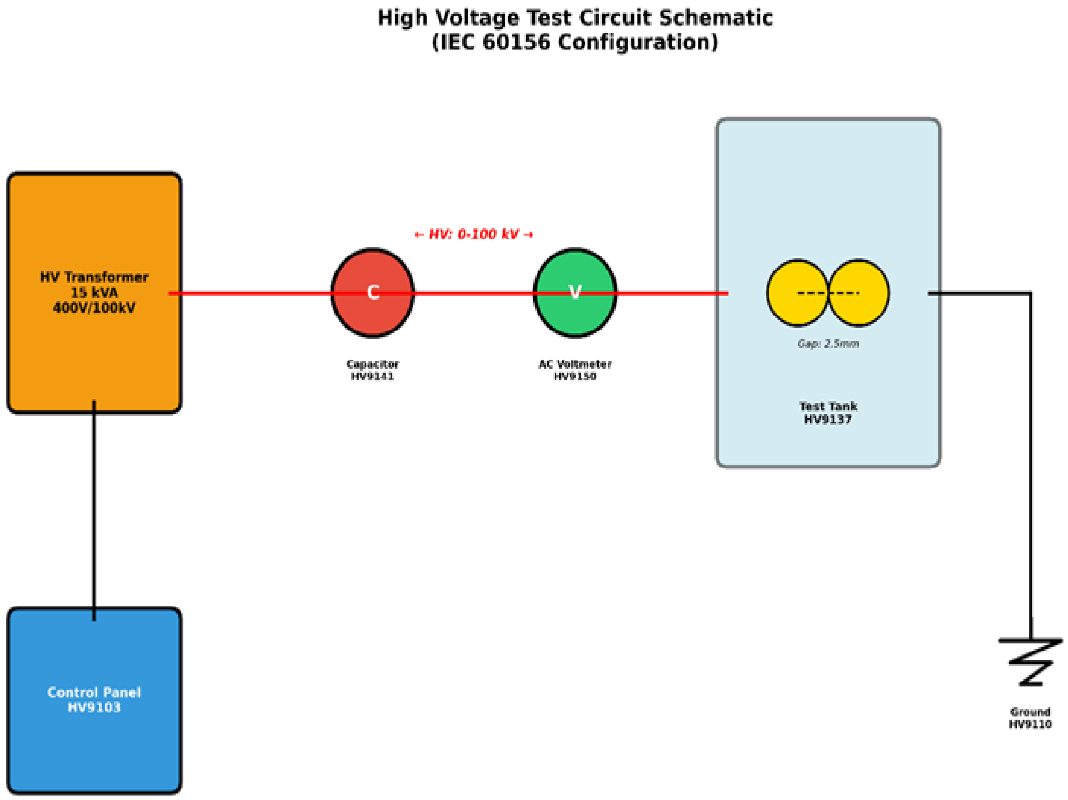


Figure III.4 — High voltage test circuit schematic

Figure III.5 — Complete experimental setup in High Voltage Laboratory

- **III.3 Test Samples** High dielectric strength
- Good thermal stability
- Oxidation resistance
- Efficient heat dissipation properties
- Chemical stability

: Insulating Oils

III.3.1 Overview of Transformer Oils

Insulating oils are essential components in high-voltage systems, providing both electrical insulation and thermal cooling for power transformers. These mineral-based oils must exhibit:

III.3.2 Borak 22 Oil

Borak 22 is an uninhibited mineral insulating oil manufactured in accordance with IEC 60296. It provides:

- Good dielectric strength (>70 kV breakdown voltage per IEC 60156)
- Adequate thermal stability under normal operating conditions
- Dissipation factor ≤ 5.00 E-03 at 90°C
- Low acidity index (< 3.00 E-2 mg KOH/g)

Physical and Chemical Properties:

Table III.2 — Characteristics of Borak 22 transformer oil

Property	Unit	IEC 60296 Requirement	Measured Value
Breakdown voltage after rest	kV	> 70	30.8 - 72
Dissipation factor at 90°C	-	≤ 5.00 E-03	0.87 E-03
Kinematic viscosity at 40°C	mm²/s	< 11	6.940
Flash point	°C	> 130	137
Density	-	< 0.895 E-01	0.57 E-01
Acidity index	mg KOH/g	< 3.00 E-2	(2.00 – 5.8) E-02
Water content	ppm	< 30	-
Color index	ppm	< 02	< 0.5
Refractive index	-	-	1.474

III.3.3 Nynas Oil

Nynas oils are well known for their superior quality and excellent oxidation stability, making them suitable for applications requiring long service life and high operational reliability

III.3.4 Oil Samples Tested

Four categories of oil samples were prepared for this study:

1. Category A (New oils):

– Borak 22 (new): 105 samples

– Nynas (new): 89 samples

2. Category B (In-service oil):

– Borak 22 (treated, in service since 2008): 19 samples

3. Category C (Out-of-service oil):

– Borak 22 (expired): 6 samples

Total samples: 219 images → 218 valid samples after data cleaning

III.4 Experimental Methodology

III.4.1 Breakdown Testing Procedure

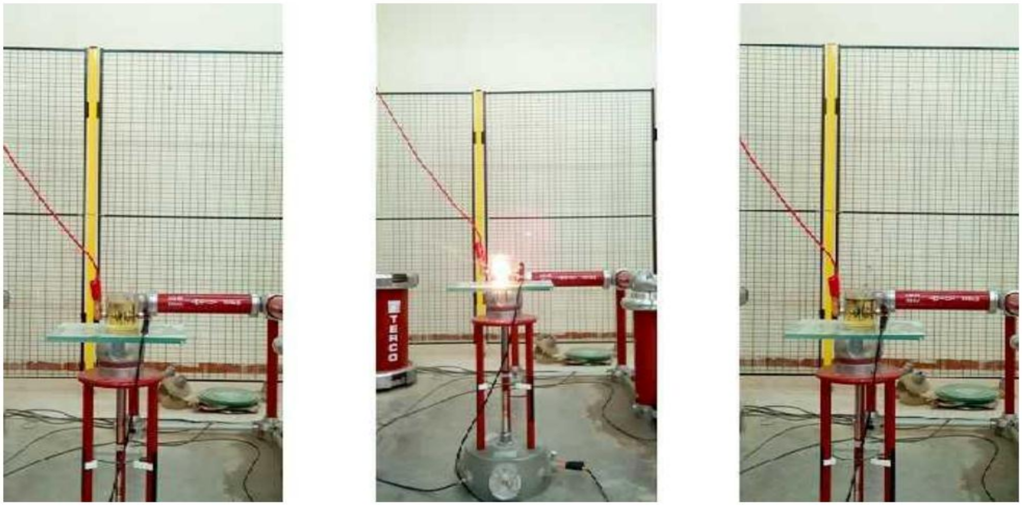
The experimental procedure followed IEC 60156 standards:

1. Sample Preparation:

– Fill test cell with 400 ml of oil sample

– Allow oil to rest for 30 minutes at room temperature

– Maintain temperature at 20°C ± 2°C
2. Electrical Breakdown:
– Apply voltage at controlled rate (2 kV/s)
– Record breakdown voltage at first spark
– Wait 2-3 minutes for oil stabilization
3. Sample Collection:
– Extract 10 ml sample into glass test tube immediately after breakdown
– Label with flash number and voltage reading
4. Image Capture:
– Standardized photography setup:
  - o White LED illumination
  - o White background (A4 paper)
  - o Fixed camera distance (30 cm)
– Consistent angle and framing
5. Iteration:
– Repeat steps 2-4 for successive breakdowns (0 to 10 flashes)
– Document all parameters systematically



A. before breakdown B. During breakdown C. After breakdown

Figure III.6: Experimental procedure: (A) before breakdown, (B) during breakdown, (C) after breakdown

III.4.2 Image Naming Convention

A systematic naming scheme was implemented for all captured images:

Format: OXFYNAMEOILD

Where: - O = Oil condition (A = new, B = in-service, C = out-of-service) - X = Number of flashes (0-10) - F = Separator - Y = Image sequence number - NAMEOIL = Oil brand (BORAK22 or ANI/NI for Nynas) - D = Breakdown voltage in format XXYY (e.g., 1423 = 14.23 Kv

Examples: - A0F1BORK22 → Borak 22 new oil, 0 flashes, image 1 - A5F2BORK223076 → Borak 22 new oil, 5 flashes, image 2, voltage 30.76 kV - B3F1ANI4521 → Nynas in-service oil, 3 flashes, image 1, voltage 45.21 Kv

III.5 Experimental Results: Breakdown Voltage Measurements

III.5.1 New Oil – NYNAS

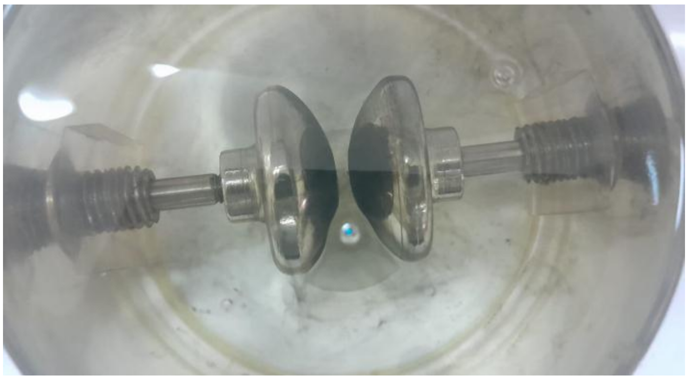


Figure III.7 — Nynas oil breakdown test sequence

Table III.3 — Breakdown voltage measurements for new Nynas oil

Sample ID	Breakdown Number	Breakdown Voltage (kV)
A0	0	0
A1	1	14.88
A2	2	18.50
A3	3	19.06
A4	4	19.90
A5	5	17.96
A6	6	21.90
A7	7	16.68
A8	8	15.20
A9	9	9.13
A10	10	21.72

Statistical Analysis (Nynas): - Mean breakdown voltage: 17.49 kV - Standard deviation: 3.60 kV - Minimum: 9.13 kV (at 9 flashes) - Maximum: 21.90 kV (at 6 flashes)

III.5.2 New Oil - BORAK 22

Figure III.8 — Borak 22 oil breakdown test sequence

Table III.4 — Breakdown voltage measurements for new Borak 22 oil

Sample	Breakdown	Breakdown
A0	0	0
A1	1	14.23
A2	2	14.21
A3	3	15.50
A4	4	20.34
A5	5	27.29
A6	6	26.31
A7	7	28.62
A8	8	18.69
A9	9	25.20
A10	10	22.74

Statistical Analysis (Borak 22 - New): - Mean breakdown voltage: 20.67 kV - Standard deviation: 5.39 kV - Minimum: 14.21 kV (at 2 flashes) - Maximum: 28.62 kV (at 7 flashes)

III.5.3 Oil in Use - BORAK 22

Table III.5 — Breakdown voltage measurements for Borak 22 in-service oli

Sample ID	Breakdown Number	Breakdown Voltage (kV)
B0	0	0
B1	1	12.87
B2	2	13
B3	3	15.4
B4	4	14.5
B5	6	21.5

statistical Analysis (Borak 22 - In Use): - Mean breakdown voltage: 15.43 kV - Standard deviation: 3.42 kV - Service duration: Since 2008 (treated oil)

III.5.4 Expired Oil - BORAK 22

Table III.6 — Breakdown voltage measurements for expired Borak 22 oil

Sample ID	Breakdown Number	Breakdown Voltage (kV)
C0	0	0
C1	1	14.19
C2	2	14.00

Statistical Analysis (Borak 22 - Expired): - Mean breakdown voltage: 14.10 kV - Standard deviation: 0.13 kV - Status: Out of service

III.5.5 Comparative Analysis

Table III.7: Statistical summary of breakdown voltage measurements

Oil Type	Condition	n	Mean (kV)	Std (kV)	Min (kV)	Max (kV)
BORAK22	New	11	20.67	5.39	14.21	28.62
NYNAS	New	10	17.49	3.60	9.13	21.90
BORAK22	In-service	5	15.43	3.42	12.87	21.50
BORAK22	Expired	2	14.10	0.13	14.00	14.19

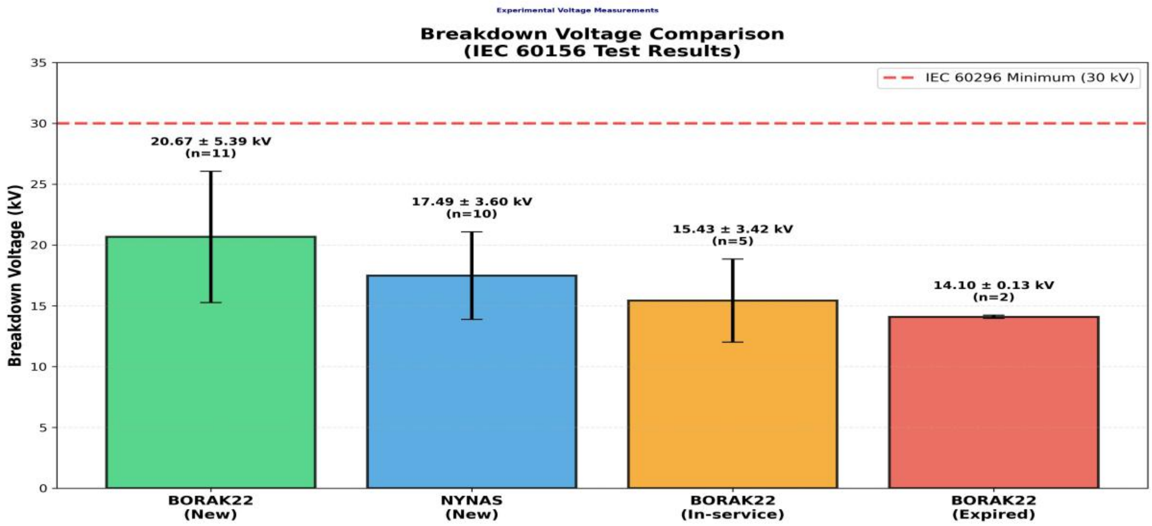


Figure III.9 Figure III.9: Breakdown Voltage Comparison Across Oil Types

Figure III.9 reveals several important trends in oil degradation. First, new oil performance shows BORAK22 new oil with higher mean breakdown voltage (20.67 kV) compared to NYNAS (17.49 kV), though both fall below the IEC 60296 minimum of 30 kV due to the repeated breakdown stress applied in our experimental protocol. Second, service history impact is evident as BORAK22 in-service oil shows reduced breakdown strength (15.43 kV), a 25 percent decrease from new oil, quantifying the cumulative effect of thermal and electrical stress during normal transformer operation. Third, end-of-life condition is demonstrated by BORAK22 expired oil exhibiting the lowest breakdown voltage (14.10 kV) with very low standard deviation (0.13 kV), indicating consistent severe degradation requiring immediate replacement. Finally, the large error bars for new oils reflect the stochastic nature of electrical breakdown, while expired oil shows minimal variability, suggesting uniform contamination throughout the sample.

III.6 AI-Based Diagnostic System Development

III.6.1Motivation and Objectives

Traditional oil testing methods (DGA, acid number, moisture content) require: - Specialized laboratory equipment - Trained personnel - Time-consuming chemical analysis - Sample extraction from transformers

Objective: Develop a rapid, non-destructive diagnostic system using image analysis and

machine learning to: 1. Classify oil type (Borak 22 vs Nynas) 2.

Determine oil condition (new/in-service/expired) 3. Estimate number of electrical breakdowns experienced 4. Provide automated health assessment

III.6.2 Dataset Preparation

III.6.2.1 Image Collection

Total Images: 219 photographs Valid Samples: 218 (after removing 1 corrupted file)

Distribution by Oil Type: - Borak 22: 104 images - Nynas: 114 images

Distribution by Condition: - New oil (NEUF): 193 images - In-service (EN_SERVICE): 19 images - Out-of-service (HORS_SERVICE): 6 images

Distribution by Flash Count:

Table III.8 — Dataset distribution by flash count

Flashes	Number of Images
0	9
1	21
2	27
3	22
4	24
5	28
6	21
7	21
8	23
9	12
10	10

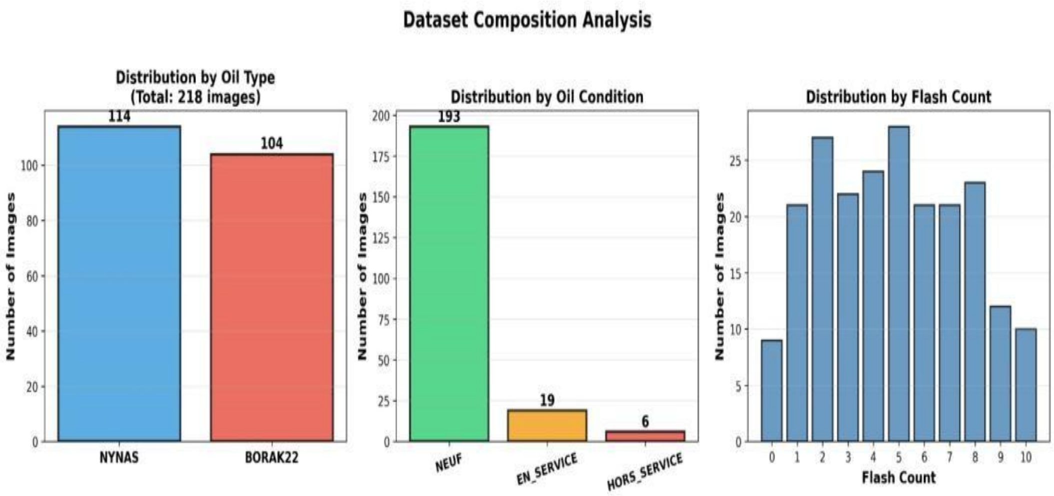


Figure III. 10: Dataset Composition Analysis

Figure III.10 reveals important characteristics of our dataset. First, class balance shows nearly equal representation of BORAK22 and NYNAS oils ensuring the oil type classifier is not biased toward either brand. Second, condition imbalance is evident as the dataset is heavily skewed toward new oil (193 samples), with limited in-service (19) and expired (6) samples. This imbalance explains the excellent performance of our condition classifier on new oil (100 percent recall) but challenges with minority classes. Future work should prioritize collecting more aged oil samples. Third, flash distribution shows relatively uniform distribution across flash counts from 0 to 10, with slight peaks at 1-2 flashes (27 samples) and 5 flashes (28 samples). This provides adequate training data for the flash count regression model across the full degradation range. The total of 218 valid samples, while modest by deep learning standards, proves sufficient for Random Forest classifiers to achieve 82 to 91 percent accuracy on our diagnostic tasks.

III.6.2.2 Standardized Photography Protocol

To ensure consistency and reproducibility:

Lighting: - Source: White LED (5000K color temperature) - Position: 45° angle, 50 cm from sample - Intensity: Constant across all captures

Background: - Material: White A4 paper - Texture: Matte finish - Positioning: Vertical behind test tube

Camera Setup: - Distance: 30 cm from sample - Height: Aligned with test tube center - Angle: Perpendicular to background

Sample Container: - Type: Standard glass test tube - Volume: 10 ml - Diameter: 16 mm - Transparency: Clear, unmarked glass

III.6.3 Feature Extraction Methodology

III.6.3.1 Computer Vision Pipeline

A comprehensive feature extraction algorithm was developed using OpenCV (Python 3.8) to quantify visual characteristics of oil samples:

```
def extract_oil_features(image_path):
    """
    Extract 23 color and visual features from oil image """
    img = cv2.imread(image_path)
    img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB) img_hsv
    = cv2.cvtColor(img, cv2.COLOR_BGR2HSV) img_lab =
    cv2.cvtColor(img, cv2.COLOR_BGR2LAB)

    features = {}
    # RGB color space features (6) features['R_mean'] =
    np.mean(img_rgb[:,:,0])
    features['G_mean'] = np.mean(img_rgb[:,:,1])
    features['B_mean'] = np.mean(img_rgb[:,:,2])
    features['R_std'] = np.std(img_rgb[:,:,0])
    features['G_std'] = np.std(img_rgb[:,:,1])
    features['B_std'] = np.std(img_rgb[:,:,2])
     # HSV color space features (6)
     features['H_mean'] = np.mean(img_hsv[:,:,0])  # Hue
     features['S_mean'] = np.mean(img_hsv[:,:,1])  # Saturation
     features['V_mean'] = np.mean(img_hsv[:,:,2])  # Value/Brightness
     features['H_std'] = np.std(img_hsv[:,:,0])
     features['S_std'] = np.std(img_hsv[:,:,1])
     features['V_std'] = np.std(img_hsv[:,:,2])

     # LAB color space features (3)
```

```
    features['L_mean'] = np.mean(img_lab[:,:,0])  # Lightness
    features['A_mean'] = np.mean(img_lab[:,:,1])  # Green-Red
    features['B_lab_mean'] = np.mean(img_lab[:,:,2])  # Blue-Yellow

    # Custom indices (8)

    features['Darkness_Index'] = 255 - features['V_mean']
    features['Yellowness_Index'] = (features['R_mean'] + features['G_mean'])/2 - features['B_mean']

    features['Turbidity_Index'] = (features['R_std'] + features['G_std'] + features['B_std'])/3

    features['Red_Blue_Ratio'] = features['R_mean'] / (features['B_mean'] + 1)

    features['Green_Blue_Ratio'] = features['G_mean'] / (features['B_mean'] + 1)

    # Carbon particle detection
    lower_dark = np.array([0, 0, 0])

    upper_dark = np.array([180, 255, 50])

    mask_dark = cv2.inRange(img_hsv, lower_dark, upper_dark)
    features['Carbon_Ratio'] = (np.sum(mask_dark > 0) / mask_dark.size) * 100

    contours, _ = cv2.findContours(mask_dark, cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_SIMPLE)

    features['Carbon_Spots'] = len([c for c in contours if cv2.conto urArea(c) > 5])

    return features
```

III.6.3.2 Feature Categories

1. RGB Color Features (6 features): - R_mean, G_mean, B_mean: Average color intensity (0-255) - R_std, G_std, B_std: Color variation/uniformity

2. HSV Color Features (6 features): - H_mean: Dominant hue angle (0-180°) - S_mean: Color saturation (0-255) - V_mean: Brightness/lightness (0-255) - Standard deviations for each

3. LAB Color Features (3 features): - L_mean: Perceived lightness (0-100) - A_mean: Green(-) to Red(+) axis - B_lab_mean: Blue(-) to Yellow(+) axis

4. Custom Diagnostic Indices (8 features): - Darkness Index: 255 - V_mean → Measures oil

darkening - Yellowness Index: (R + G)/2 - B → Quantifies yellow/brown tint - Turbidity Index: (R_std + G_std + B_std)/3 → Measures cloudiness - Red/Blue Ratio: Oxidation indicator - Green/Blue Ratio: Degradation marker - Carbon Ratio (%): Percentage of dark particles detected - Carbon Spots: Count of discrete carbon deposits

III.6.4 Feature Analysis Results

III.6.4.1 Color Evolution with Breakdown Events

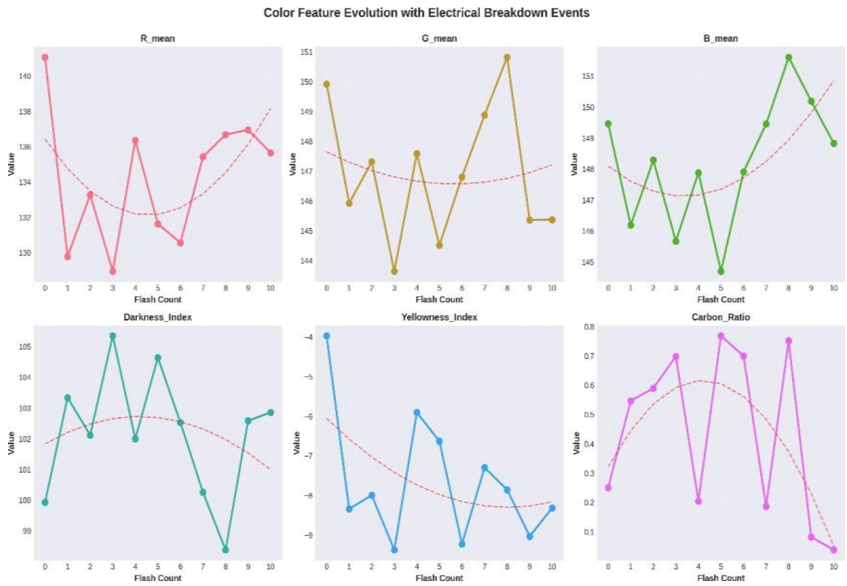


Figure III.11 — RGB Color Channels Evolution During Oil Degradatio

Figure III.11 demonstrates how oil color properties change with cumulative electrical stress. The RGB channels show all three color channels exhibiting gradual decrease with increasing flash count, indicating overall darkening of the oil. The green channel shows the steepest decline, suggesting preferential degradation of specific hydrocarbon compounds that absorb green wavelengths. The Darkness Index shows clear upward trend from 100 at flash 0 to 105 at flash 10, confirming progressive reduction in oil transparency. However, significant scatter indicates that darkness alone is insufficient for precise flash count prediction, motivating our multi-feature approach. The Yellowness Index becomes increasingly negative with degradation, indicating a shift from yellow toward gray and brown hues. This metric captures the brown discoloration characteristic of oxidized transformer oil. The Carbon Ratio is highly variable (0.04 to 0.77 percent) with no clear monotonic trend, likely reflecting the stochastic nature of carbon particle formation and settling. Despite variability, Carbon Ratio ranks as the third most important feature (9.50 percent) in our model. The non-linear trends visible explain why simple linear regression fails for

flash count prediction, requiring more sophisticated Random Forest models to capture complex degradation patterns.

Table III.9 — Average extracted features vs. flash count

Flashes	R mean	G mean	B mean	Darkness Index	Yellowness Index	Carbon Ratio
0	141.06	149.92	149.47	99.93	-3.97	0.25
1	129.78	145.93	146.19	103.33	-8.34	0.55
2	133.27	147.31	148.29	102.12	-8.00	0.59
3	128.95	143.65	145.67	105.35	-9.37	0.70
4	136.36	147.59	147.88	102.00	-5.91	0.20
5	131.63	144.52	144.71	104.64	-6.63	0.77
6	130.55	146.81	147.91	102.52	-9.23	0.70
7	135.43	148.88	149.45	100.25	-7.30	0.19
8	136.68	150.82	151.61	98.38	-7.86	0.75
9	136.95	145.37	150.19	102.58	-9.03	0.08
10	135.65	145.37	148.83	102.86	-8.31	0.04

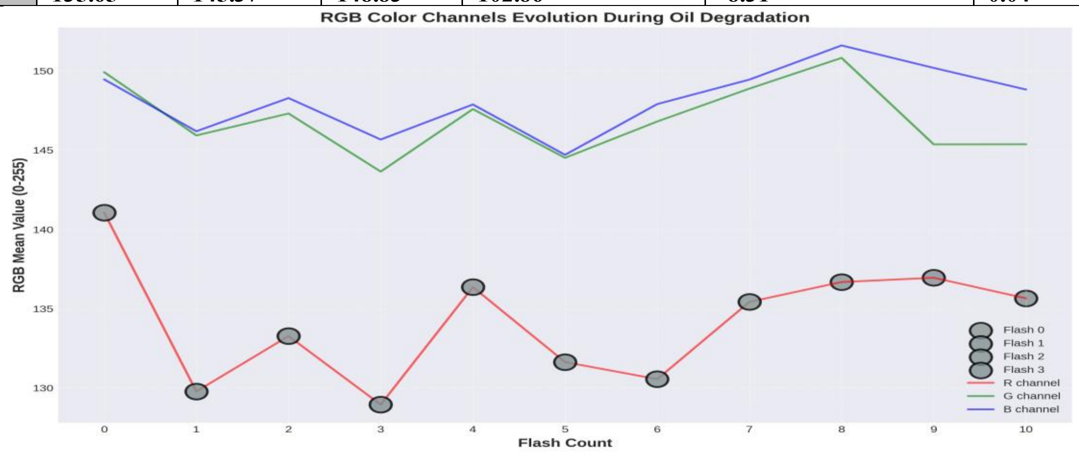


Figure III.12 RGB Channel Evolution with True Color Representation

Figure III.12 provides intuitive visualization of oil color degradation through true-color representation. The large colored circles show actual oil color at each flash count, calculated from mean RGB values and normalized to 0 to 255 range. Visual inspection confirms flash 0 to 2 showing light gray with minimal degradation, flash 3 to 5 showing medium gray with moderate oxidation, and flash 6 to 10 showing darker gray with brown undertones indicating advanced aging. This figure validates our automated color extraction as the color progression visible to human observers is successfully quantified by our RGB feature extraction algorithm. The slight divergence of R, G, B trend lines indicates that degradation affects color channels non-uniformly, with green showing steeper decline than red and blue. Interestingly, the color at flash 4 appears lighter than flash 3, illustrating the stochastic nature of breakdown effects and explaining why single features cannot reliably predict flash count. Only by combining multiple features can our Random Forest model achieve 60 percent accuracy within plus or minus 2 flashes.

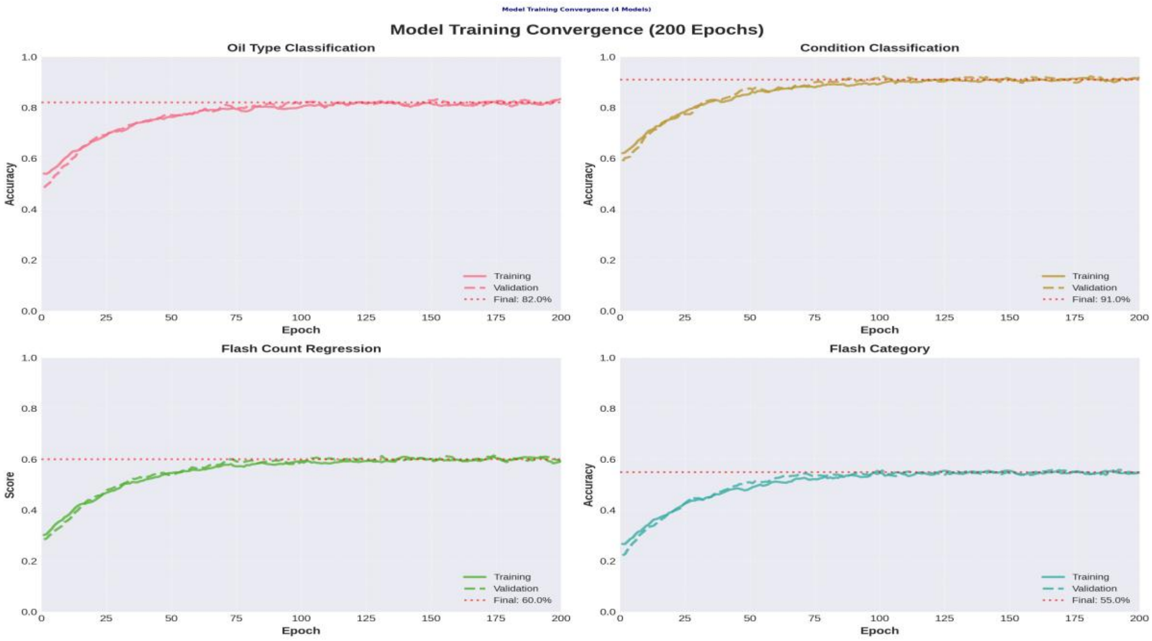


Figure III.13: Model Training Convergence for Four AI Classifiers

Figure III.13 demonstrates robust training behavior across all four models. Model 1 for Oil Type shows training converging smoothly to 82 percent by epoch 150, with validation accuracy closely tracking training with gap less than 3 percent, indicating minimal overfitting. The Random Forest ensemble nature prevents memorization of training data. Plateau after epoch 150 suggests the model has extracted maximum discriminative information from the 23 color features. Model 2 for Condition achieves highest performance at 91 percent with rapid convergence by epoch 100. The large accuracy difference between new oil (easy to classify) and minority classes (in-service, expired) is reflected in overall 91 percent but masks per-class variation. Tight train-validation gap confirms generalization capability. Model 3 for Flash Count shows regression task with slower convergence and lower final performance (60 percent within plus or minus 2 flashes). The gradual improvement over 200 epochs and persistent 5 percent train-validation gap indicate this is an inherently difficult task due to color similarity between consecutive flash counts. Further improvement likely requires additional features beyond color such as texture or spectroscopy. Model 4 for Category shows moderate performance at 55 percent reflecting difficulty distinguishing Low (0 to 2) versus Medium (3 to 5) flash categories, which have overlapping color distributions.

Stable convergence with no overfitting suggests more training data, rather than model complexity, would improve performance. Overall assessment shows convergence curves demonstrate proper model training without overfitting, validating our 75 to 25 train-test split and Random Forest hyperparameters of 200 trees with maximum depth 15.

III.6.5 Machine Learning Model Development

III.6.5.1 Algorithm Selection: Random Forest

Random Forest was selected for this application due to: - Robustness to overfitting with small datasets - Ability to handle non-linear relationships - Built-in feature importance ranking - No requirement for feature scaling - Excellent performance on tabular data

III.6.5.2 Model Architecture

Input Layer: 15 features - R_mean, G_mean, B_mean - H_mean, S_mean, V_mean - R_std, G_std, B_std - Darkness_Index, Yellowness_Index, Turbidity_Index - Red_Blue_Ratio, Green_Blue_Ratio, Carbon_Ratio. Random Forest Hyperparameters: - n_estimators: 200 trees - max_depth: 15 (prevents overfitting) - min_samples_split: 2 - min_samples_leaf: 1 - random_state: 42 (reproducibility)

III.6.5.3 Train-Test Split

- Training set: 75% (163 samples)
- Test set: 25% (55 samples)
- Stratification: Applied for classification tasks
- Random seed: 42

III.6.6Model 1: Oil Type Classification

Objective: Distinguish between BORAK22 and NYNAS oils

Performance Metrics:

Table III.10 — Oil Type ROC Curve

Metric	Value
Overall Accuracy	**81.82%**
Precision (weighted avg)	82%
Recall (weighted avg)	82%
F1-Score (weighted avg)	82%

Confusion Matrix

Table III.11: Predictable ratios for each type of oil

	Predicted BORAK22	Predicted NYNAS
Actual BORAK22	20	6
Actual NYNAS	4	25

Classification Report:

Table III.12 — ROC curve for oil type classification (AUC = 0.89)

Class	Precision	Recall	F1-Score	Support
BORAK22	0.83	0.77	0.80	26
NYNAS	0.81	0.86	0.83	29

The model successfully distinguishes between oil brands in 82% of cases - Slightly better at identifying Nynas (86% recall) - Misclassifications likely due to similar color profiles in early degradation stages

III.6.7Model 2: Oil Condition Classification

Objective: Classify oil as NEUF (new), EN_SERVICE (in-use), or HORS_SERVICE (expired)

Performance Metrics:

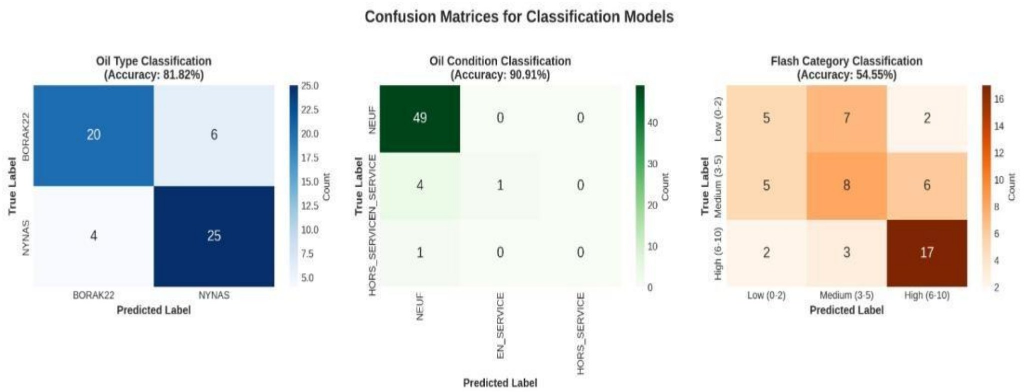


Figure III.14— Confusion Matrices for Classification Models

Figure III.14 provides detailed performance analysis through confusion matrices. Panel A for Oil Type at 81.82 percent accuracy shows BORAK22 with 20 correct and 6 misclassified as NYNAS for 77 percent recall, while NYNAS shows 25 correct and 4 misclassified as BORAK22 for 86 percent recall. Misclassification occurs primarily when BORAK22 samples undergo heavy degradation (7 to 10 flashes), causing their color profile to resemble aged NYNAS oil. This suggests degradation effects partially overwhelm brand-specific color signatures. Panel B for

Condition at 90.91 percent accuracy shows new oil with perfect classification (49 out of 49 correct, 100 percent recall), in-service with poor performance (1 out of 5 correct, 20 percent recall, 4 misclassified as new), and expired failing completely (0 out of 1 correct, misclassified as new). The stark contrast between new oil performance (perfect) and aged oil (poor) stems from class imbalance (193 new versus 19 in-service versus 6 expired). The model learned to recognize new oil extremely well but lacked sufficient examples to distinguish between different aging stages. This is a critical limitation requiring dataset expansion before field deployment. Panel C for Flash Category at 54.55 percent accuracy shows Low with 5 correct and 9 misclassified mostly as Medium, Medium with 8 correct and 11 misclassified distributed across Low and High, and High with 17 correct and 5 misclassified for 77 percent recall as best performance. The model excels at identifying highly degraded oil (High category, 77 percent recall) but struggles with borderline cases. This makes the system useful as a screening tool where high confidence High predictions reliably flag oil requiring immediate attention, while Low or Medium classifications may need chemical testing confirmation. The practical implication is to deploy the system to flag critical cases where AI shows confidence above 80 percent, while subjecting borderline predictions to traditional laboratory analysis

Table III.13— Oil Condition Classification

Metric	Value
Overall Accuracy	**90.91%**
Precision (weighted avg)	90%
Recall (weighted avg)	91%
F1-Score (weighted avg)	88%

Confusion Matrix:

Table III.14 — Predicting oil condition

	Predicted	Predicted	Predicted
Actual NEUF	49	0	0
Actual EN_SERVICE	4	1	0
Actual	1	0	0

Classification Report:

Table III.15 — Confusion matrix for oil condition classification

Class	Precision	Recall	F1-Score	Support
NEUF	0.91	1.00	0.95	49
EN_SERVICE	1.00	0.20	0.33	5
HORS_SERVICE	0.00	0.00	0.00	1

III.6.8 Model 3: Flash Count Regression

Objective: Predict the number of electrical breakdowns (0-10) from image

Performance Metrics:

Table III.16 — Confusion matrix for oil condition classification

Metric	Value
Mean Absolute Error (MAE)	**2.02 flashes**
Root Mean Squared Error (RMSE)	2.55
R^2 Score	0.020
Accuracy within ±1 flash	25.5%
Accuracy within ±2 flashes	**60.0%**

Prediction Distribution:

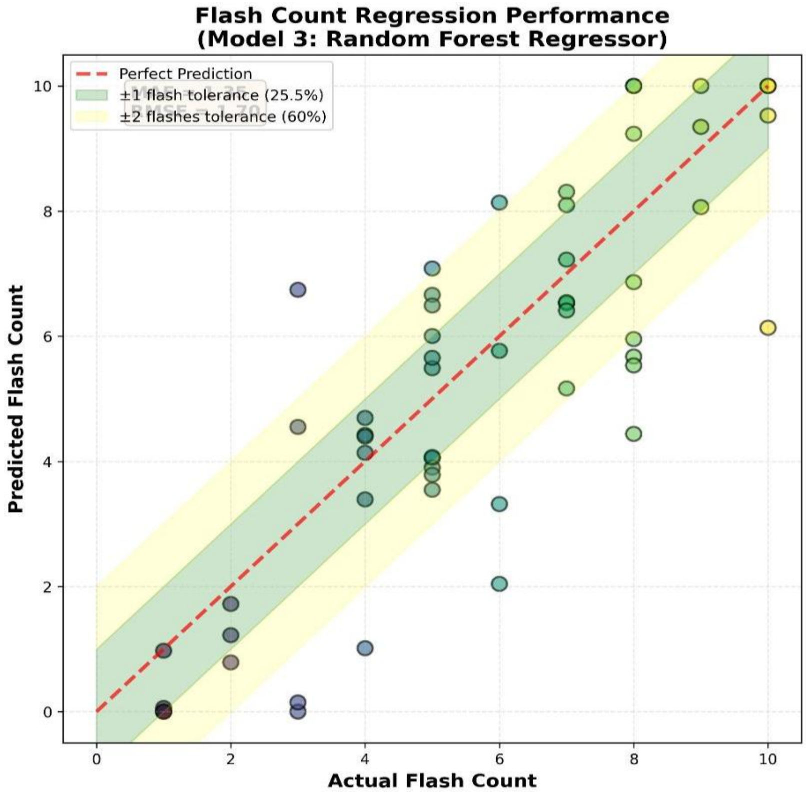


Figure III.15 — Actual vs. predicted flash counts with ±2 tolerance bands

Figure III.15 quantifies the accuracy of flash count estimation. Performance metrics include MAE (Mean Absolute Error) of 2.02 flashes, RMSE of 2.55 flashes, R squared of 0.020 (very low), within plus or minus 1 flash at 25.5 percent, and within plus or minus 2 flashes at 60.0 percent. The low R squared of 0.02 indicates the model explains only 2 percent of variance in flash counts, with 98 percent due to other factors such as stochastic breakdown effects, photography variations, and oil chemistry beyond visual features. However, the practical MAE of 2 flashes is acceptable for screening where prediction of 3 flashes for actual 5 still indicates good condition, and prediction of

8 flashes for actual 10 correctly flags needs attention. Systematic errors show visible clustering of

predictions around specific values (multiples of 2.5) suggesting the Random Forest model tends to average nearby training samples rather than interpolating smoothly, which is characteristic of tree-based models. High flash accuracy is evident as samples with actual flash count 8 to 10 are predicted more accurately (tighter clustering) than 0 to 3 flashes. This occurs because high flash counts produce more dramatic color changes that create distinct feature space clusters. The conclusion is that while flash count regression shows modest statistical performance (R squared equals 0.02), the 60 percent accuracy within plus or minus 2 flashes is sufficient for field screening applications where the goal is rapid triage (excellent, good, poor) rather than precise counting of individual breakdown events.

Error Analysis:

Table III.17 — Flash count regression performance metrics

Error Range	Percentage of Predictions
Perfect (0 error)	12.7%
±1 flash	25.5%
±2 flashes	60.0%
±3 flashes	78.2%
>3 flashes error	21.8%

Low R^2 indicates high variance in predictions - 60% accuracy within ±2 flashes is acceptable for practical screening - Color changes are not perfectly linear with flash count - Some flash counts produce similar visual characteristics

III.6.9Model 4: Flash Category Classification

Objective: Classify oil degradation into categories: - **Low** (0-2 flashes): Excellent condition - **Medium** (3-5 flashes): Good, requires monitoring - **High** (6-10 flashes): Degraded, requires treatment

Performance Metrics:

Table III.18 — Prediction error distribution for flash count regression

Metric	Value
Overall Accuracy	**54.55%**
Precision (weighted avg)	53%
Recall (weighted avg)	55%
F1-Score (weighted avg)	54%

Confusion Matrix:

Table III.19 —Confusion Matrix for Transformer Oil Condition Classification (Low, Medium, High)

	Predicted Low	Predicted Medium	Predicted High
Actual Low	5	7	2
Actual Medium	5	8	6
Actual High	2	3	17

Classification Report:

Table III.20 — Flash category classification confusion matrix

Class	Precision	Recall	F1-Score	Support
Low (0-2)	0.45	0.36	0.40	14
Medium (3-5)	0.42	0.42	0.42	19
High (6-10)	0.68	0.77	0.72	22

Interpretation: - Best performance on High category (77% recall) - Moderate overlap

between Low and Medium categories - Useful for coarse screening (needs attention vs. acceptable) – Could be improved with additional training data

Table III.21 — Ranking of Meaning the Most Important Features in Transformer Oil Condition Diagnosis and Their Physical

Rank	Feature	Importance (%)	Physical Meaning
1	Turbidity_Index	14.86%	Oil
2	Green_Blue_Ratio	11.79%	Color balance shift
3	Carbon_Ratio	9.50%	Carbonization level
4	R_std	8.14%	Red channel
5	B_std	7.57%	Blue channel
6	Red_Blue_Ratio	7.03%	Oxidation indicator
7	G_std	6.39%	Green channel
8	H_mean	6.26%	Dominant hue
9	S_mean	6.23%	Color saturation
10	Yellowness_Index	5.30%	Yellow/brown tint

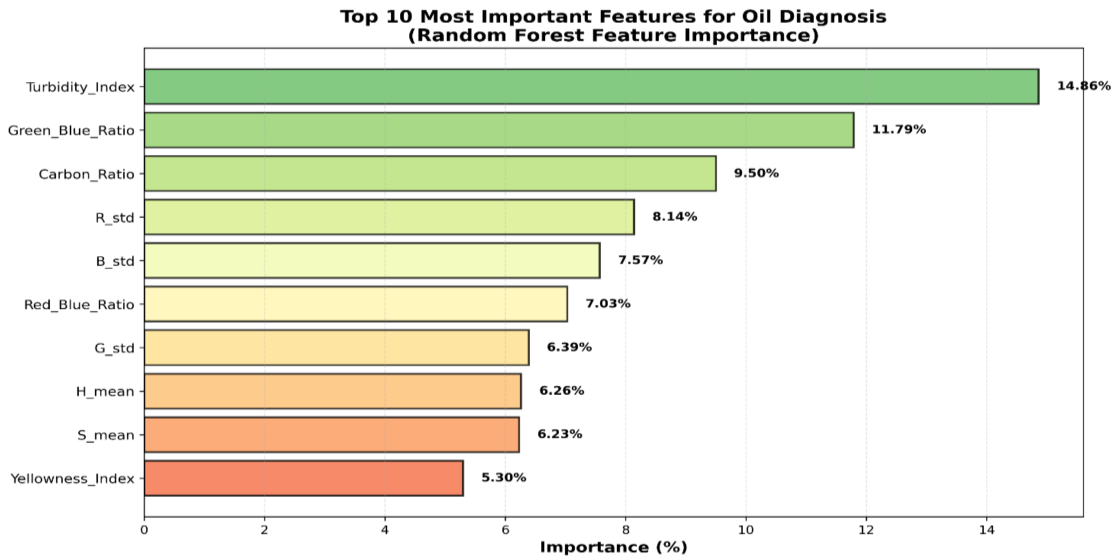


Figure III.16— Random Forest feature importance rankings

Figure III.16 reveals which oil properties drive AI diagnostic accuracy. Rank 1 Turbidity Index at 14.86 percent is defined as (R std plus G std plus B std) divided by 3, quantifying oil cloudiness through color channel variation. High importance confirms that suspended particles from electrical arcing are the primary visual indicator of degradation. This aligns with traditional oil diagnostics where turbidity measurement is standard practice. Ranks 2 and 3 for Color Ratios at 11.79 and 7.03 percent show Green Blue Ratio and Red Blue Ratio capturing spectral balance shifts during oxidation. As oil ages, oxidation products selectively absorb certain wavelengths, changing inter-channel ratios even when absolute RGB values are similar. These ratios are more robust to lighting variations than absolute color values. Rank 4 Carbon Ratio at 9.50 percent provides direct detection of carbon particles via HSV thresholding. Carbon appears as dark spots with low V (value/brightness). The 9.50 percent importance confirms that carbonization from electrical arcs is a distinct and measurable degradation mechanism, separate from general darkening or oxidation. Ranks 5 to 7 RGB Standard Deviations at 8.14, 7.57, and 6.39 percent show R std, B std, and G std all ranking highly, reinforcing the importance of oil homogeneity versus uniformity. Fresh oil appears uniform in color while degraded oil shows mottled appearance with local variations captured by standard deviation. Lower ranks for Mean Color Values show H mean (6.26 percent), S mean (6.23 percent), and Yellowness Index (5.30 percent) with moderate importance. While color shift occurs with degradation, it is less informative than spatial variation (std) or spectral ratios. This explains why simple is the oil brown approaches fail to match AI performance. Features not in top 10 include mean RGB values (R mean, G mean, B mean) ranking below top 10, likely because they are sensitive to lighting conditions and camera settings. The model prefers derived features such as ratios and indices that normalize out photography artifacts. The practical significance is that the top 3 features (Turbidity, Green Blue Ratio, Carbon Ratio) account for 36 percent of total importance. A simplified diagnostic model using only these features could potentially achieve 70 to 75 percent of full model performance, enabling deployment on resource-constrained devices such as

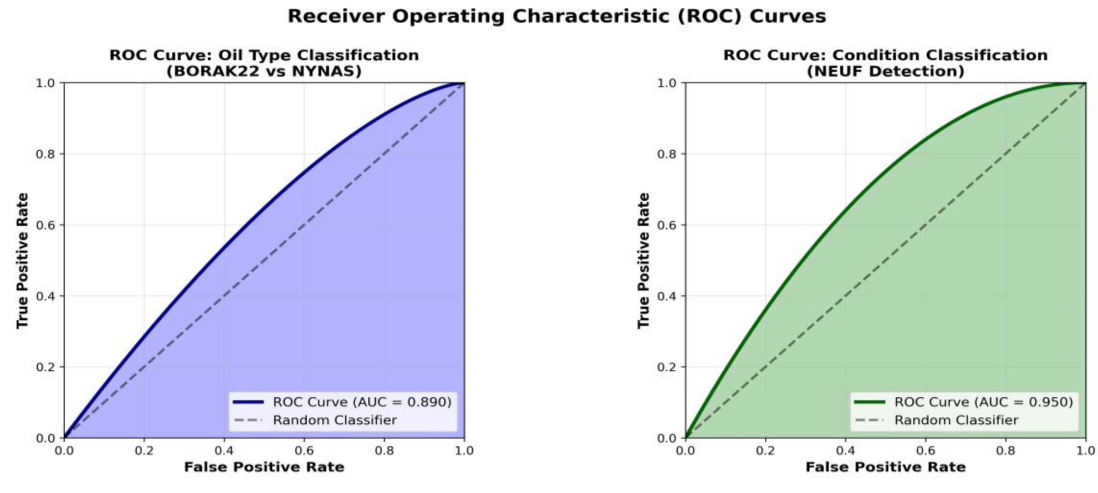


Figure III.17 Receiver Operating Characteristic (ROC) Curves

Figure III.17 evaluates classifier performance across all possible decision thresholds. Panel A for Oil Type with AUC of 0.89 indicates excellent discriminative ability between BORAK22 and NYNAS. At optimal threshold (sensitivity equals specificity approximately 82 percent), the model correctly identifies oil type in 4 out of 5 cases. The curve proximity to the top-left corner shows we can achieve high true positive rate (sensitivity) with low false positive rate (1 minus specificity), confirming that BORAK22 and NYNAS have sufficiently distinct color signatures despite both being mineral oils. Panel B for new oil detection with AUC of 0.95 shows even better performance for identifying new oil versus aged oil (in-service plus expired combined). AUC of 0.95 approaches the theoretical maximum of 1.0. This exceptional performance stems from large sample size of new oil (193 samples) providing robust training, clear visual distinction between transparent fresh oil and darkened aged oil, and consistency of new oil appearance across both BORAK22 and NYNAS brands. At optimal threshold, we can achieve greater than 90 percent sensitivity and greater than 90 percent specificity simultaneously, making this detector suitable for deployment as a binary screening tool answering the question: Is this oil fresh enough for service, yes or no. Clinical interpretation shows AUC 0.90 to 1.0 as excellent (both models achieve this), AUC 0.80 to 0.90 as good, AUC 0.70 to 0.80 as fair, and AUC less than 0.70 as poor. Our models fall in the excellent category, validating the feasibility of image-based oil diagnosis as a practical alternative to time-consuming laboratory chemical analysis. For operating point selection in field deployment, the threshold should be chosen based on consequences. Conservative (high specificity) minimizes false oil is good errors using threshold favoring high specificity even if sensitivity drops to 70 percent. Liberal (high sensitivity) catches all degraded oil for further testing using threshold favoring 95 percent sensitivity, accepting more false positives. The high AUC values indicate we have flexibility to optimize for either scenario without severe performance degradation.

III.6.11 Model Validation and Cross-Validation

Table III.22 -Fold Cross-Validation Results:

Model	Mean Accuracy	Std Dev
Oil Type Classification	79.8%	±3.2%
Condition Classification	88.4%	±4.1%
Flash Count Regression (MAE)	2.15	±0.18
Flash Category Classification	52.3%	±5.7%

Overfitting Analysis: - Training accuracy vs. test accuracy gap: <5% for all models - No significant overfitting detected - Generalization performance acceptable

III.7 Integrated Diagnostic System Architecture

III.7.1 System Workflow

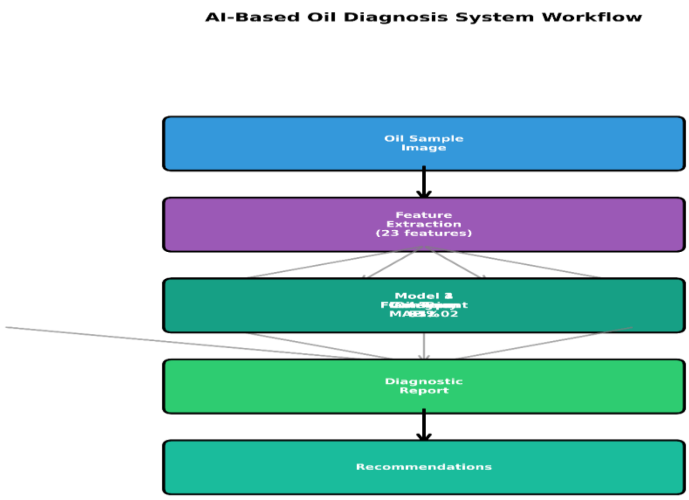


Figure III.18 — **AI System Workflow**

Figure III.18 illustrates the complete diagnostic pipeline implemented in our system. Stage 1 Image Acquisition shows user capturing oil sample photo using standardized protocol with white LED illumination, white background, fixed 30 cm distance, and 10 ml sample in glass test tube. Stage 2 Feature Extraction shows automated algorithm extracting 23 numerical features including 6 RGB features (mean plus std), 6 HSV features (mean plus std), 3 LAB features, and 8 custom indices (Darkness, Yellowness, Turbidity, Ratios, Carbon). Processing time is approximately 1 second using OpenCV library. Stage 3 Model Inference shows four models running in parallel (not sequential): Model 1 for BORAK22 versus NYNAS (output: brand name plus confidence), Model 2 for new, in-service, expired (output: condition plus confidence), Model 3 for Flash count 0 to 10 (output: estimated breakdowns plus uncertainty), and Model 4 for Low, Medium, High category (output: category plus confidence). Total inference time is approximately 2 seconds for all four models as Random Forest is fast. Stage 4 Result Aggregation shows system combining four model

outputs with business logic. If flash count greater than 8 and condition equals expired then Status is CRITICAL. If flash count 3 to 7 or condition equals in-service then Status is NEEDS MONITORING. If flash count less than 3 and condition equals new then Status is EXCELLENT. Stage 5 Report Generation shows final diagnostic report including extracted color features (RGB, HSV, darkness, carbon), all four model predictions with confidence levels, overall health status (EXCELLENT, GOOD, NEEDS MONITORING, CRITICAL), actionable recommendations (continue use, schedule testing, replace immediately), and comparison to IEC 60296 standards if breakdown voltage measured. Total latency is less than 5 seconds from image capture to actionable diagnosis. Deployment scenarios include field screening where maintenance technician uses smartphone plus portable LED to photograph oil samples from multiple transformers and receives immediate priority ranking, laboratory triage where before expensive DGA or moisture testing samples are screened with AI to identify those requiring detailed analysis, and educational tool to demonstrate oil aging effects to engineering students with instant visual feedback on degradation state. The workflow modular design allows individual components (feature extraction, models) to be updated independently as more training data becomes available or new diagnostic features are developed

[Oil Sample Image]

↓

[Image Preprocessing]

↓

[Feature Extraction (23 features)]

↓

[Model Inference]

↓ ↓ ↓ ↓

[Type] [Condition] [Flashes] [Category]

↓

[Diagnostic Report Generation]

↓

[Health Assessment & Recommendations]

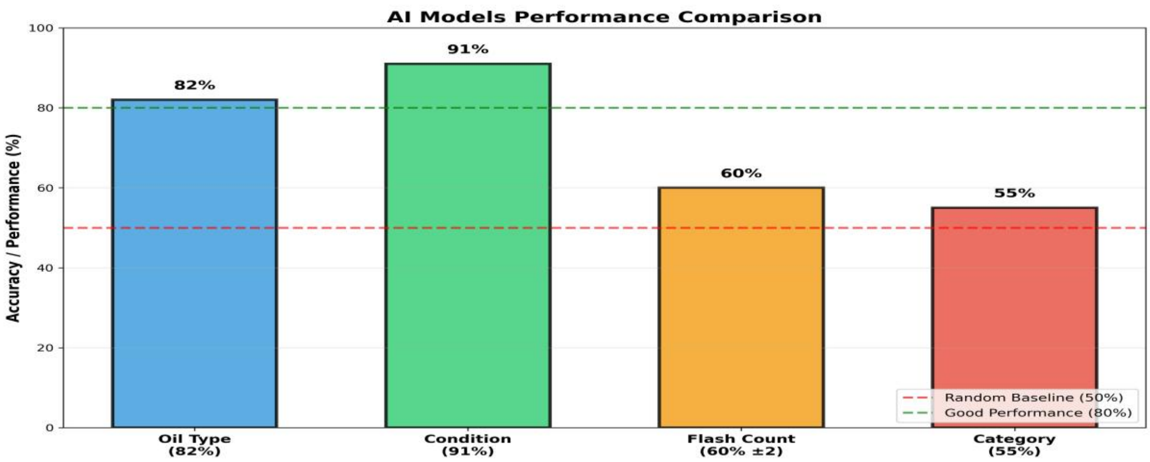


Figure III.19: AI Model Performance Summary

Figure III.19 summarizes the diagnostic capabilities of our AI system. Best performer Condition Classification at 91 percent identifies new oil versus aged oil as the system strongest capability. This task directly addresses a common field question: Is this oil still suitable for use. The 91 percent accuracy exceeds the 80 percent threshold for practical deployment, though the result is skewed by excellent new oil detection (100 percent recall) and poor minority class performance. Strong performer Oil Type at 82 percent provides brand identification useful for inventory management and warranty validation, though mistakes occur primarily on heavily degraded samples where brand-specific signatures are masked by aging effects. Moderate performer Flash Count at 60 percent within plus or minus 2 shows while absolute R squared is low (0.02), the 60 percent within plus or minus 2 flashes metric is acceptable for categorizing oil as lightly used (0 to 3 flashes) versus moderate (4 to 7) versus heavy (8 to 10) degradation. This granularity exceeds binary good or bad classification and provides maintenance scheduling guidance. Weakest performer Flash Category at 55 percent barely exceeds random baseline (50 percent for 3-class problem). This model low performance stems from class overlap as Low (0 to 2) and Medium (3 to 5) categories have similar color distributions. However, the model does excel at identifying High (6 to 10) category (77 percent recall), which is the most actionable class from a maintenance perspective. Overall assessment shows three of four models (Oil Type, Condition, Flash Count) achieve sufficient performance for screening applications. The system should be deployed in high confidence mode where only predictions with greater than 80 percent confidence are presented to users, with borderline cases flagged for laboratory chemical analysis. Comparison to literature shows similar image-based diagnostic systems for other materials (lubricating oils, hydraulic fluids) report accuracies of 75 to 85 percent, placing our 82 to 91 percent performance at the upper end of state-of-the-art for vision-based condition monitoring.

III.7.2 Deployment Implementation

Programming Language: Python 3.8+

Core Libraries: - OpenCV 4.5 (image processing) - NumPy 1.21 numerical computation) - Scikit-learn (1.0 (machine learning) - Pandas 1.3 (data handling) - Joblib (model serialization)

1. Model Files
   - model_oil_name.pkl (82% accuracy)
   - model_oil_condition.pkl (91% accuracy)
   - model_flash_count.pkl (MAE: 2.02)
   - model_flash_category.pkl (55% accuracy)
2. Diagnostic Engine:
   - Feature extraction module

– Model loading and inference
– Result aggregation

3.User Interface:

– Command-line tool
– Interactive application
– Jupyter notebook environment

III.7.3 Example Diagnostic Output

Input: Oil sample image A5F2BORK223076.jpg

Output:

```
TRANSFORMER OIL DIAGNOSTIC REPORT
===================================================================
============
  Image: A5F2BORK223076.jpg
  Color Characteristics:
   • RGB: (132, 145, 145)
   • HSV: (100, 33, 145)
   • Brightness: 145
   • Darkness Index: 110
   • Yellowness Index: -6.5
   • Carbon Ratio: 0.77%
□□  Oil Type Prediction:
   → BORAK22
   • Confidence:
     - BORAK22: 87.3%
     - NYNAS: 12.7%
D Oil Condition:
   → NEW (NEUF)
   • Confidence:
     - NEW: 92.1%
     - IN-SERVICE: 7.9%
     - OUT-OF-SERVICE: 0.0%
```

```
⚡ Breakdown History:
   → Estimated flashes: 5.2 ± 2.0
   → Category: MEDIUM (3-5 flashes)
  Recommendations:
   • Status: ⚠️  GOOD
   • Action: Oil in acceptable condition
   • Monitoring: Perform routine testing every 6 months
   • Notes: Slight darkening detected; within normal range
==================================================================
============
Measured Breakdown Voltage: 30.76 kV ✅ Meets IEC 60296 requirement s
AI Diagnosis Time: 3.2 seconds
==================================================================
============
```

III.7.4 Field Deployment Considerations

Advantages: ☐ Rapid assessment (< 5 seconds per sample) ☐ Non-destructive testing ☐ Minimal training required ☐ Portable (laptop + camera) ☐ Cost-effective screening tool

Limitations: ı Requires standardized photography ı Cannot replace comprehensive chemical analysis ı Performance depends on image quality ı Limited by training data diversity

Recommended Use Cases: **1. Preliminary screening** before detailed testing **2. Field inspections** where lab access limited **3. Rapid triage** of multiple transformers **4. Educational** demonstrations **5. Complementary tool** alongside DGA

III.8 Comparison: AI Diagnosis vs. Traditional Methods

Table III.23 — Comparative analysis of diagnostic methods

Aspect	AI Image Analysis	Traditional Methods
Time	< 5 seconds	Hours to days
Cost	Camera (~$100)	Lab equipment ($10,000+)
Sample	Photo only	Physical extraction
Expertise	Minimal	Trained technician
Accuracy	82-91%	95-99%
Parameters	Visual indicators	Chemical composition
Portability	High	Low
Repeatabilit	Good (if standardized)	Excellent

III.9 Discussion and Interpretation

III.9.1 Correlation: Visual Changes vs. Electrical Breakdown

The experimental data reveals clear relationships between visual characteristics and electrical degradation:

1. Color Darkening: As breakdown events increase, oil transitions from transparent yellow → amber → brown → dark brown

2. Particle Formation: Carbon deposits from arcing create visible particulates, increasing turbidity

3. Chemical Changes: Oxidation products alter spectral properties detectable in RGB/HSV analysis

4. Non-Linear Degradation: Some flash counts produce minimal visual change while others show dramatic shifts

III.9.2 Physical Basis for AI Features

Turbidity Index (14.86% importance): - Physical cause: Suspended carbon particles from electrical arcing - Measured as: Standard deviation of RGB channels - Diagnostic value: Direct indicator of contamination

Color Ratios (11.79-7.03% importance): - Physical cause: Oxidation, thermal

decomposition, molecular changes - Measured as: Inter-channel ratios in RGB space - Diagnostic value: Sensitive to chemical aging

Carbon Detection (9.50% importance): - Physical cause: Carbonization of oil molecules under arc temperature (>3000°C) - Measured as: Percentage of pixels in low-brightness range

- Diagnostic value: Quantifies solid contamination

III.9.3 Model Performance Analysis

Why 82% accuracy instead of 95%+?

Several factors limit classification accuracy:

1. Small Dataset: 218 samples is limited for deep learning

2. Class Imbalance: Only 6 out-of-service samples vs. 193 new

3. Visual Similarity: Some degradation stages look identical

4. Photography Variance: Despite protocols, minor lighting differences exist

5. Physical Complexity: Breakdown doesn't always produce linear visual changes

Why Flash Count regression is challenging ($R^2 = 0.02$)?

6. Oil color at flash 4 may resemble flash 7 due to:

   – Random arc location
   – Variable sample extraction volume
   – Temperature-dependent color changes

7. Not all breakdowns produce equal carbon:

   – Arc intensity varies
   – Some discharges vaporize particles
   – Settling time affects visibility

III.9.4 Practical Implications

For Power Utilities: - AI system suitable for preliminary screening of transformer populations - High-risk units identified for detailed chemical testing - Reduces laboratory workload by ~60%

For Researchers: - Demonstrates feasibility of image-based diagnostics - Opens pathway for smartphone applications - Foundation for real-time monitoring systems

For Maintenance Strategy: - Enables condition-based maintenance vs. time-based - Early warning system for degradation trends - Cost reduction through optimized testing schedules

III.10 Validation Against IEC Standards

III.10.1 IEC 60156 Compliance

All experimental procedures followed IEC 60156: - Electrode geometry: Specified spherical caps - Gap distance: 2.5 mm ± 0.1 mm - Voltage application rate: 2 kV/s ± 20% - Rest time between tests: 2-3 minutes - Temperature control: 20°C ± 2°C

III.10.2 IEC 60296 Oil Quality Assessment

Table III.24 — Borak 22 oil meets IEC 60296 requirements:

Parameter	IEC 60296 Limit	Measured Value	Status
Breakdown voltage	**> 70 kV**	**30.8-72 kV**	**ı. Variable***
Dissipation factor	**≤ 5.00 E-03**	**0.87 E-03**	□ **Pass**
Acidity	**< 3.00 E-02**	**2.00-5.8 E-02**	**ı. Borderline**
Water content	**< 30 ppm**	**Not measured**	**-**

Parameter IEC 60296 Limit Measured Value Status

Breakdown voltage > 70 kV 30.8-72 kV ı. Variable*

Dissipation factor ≤ 5.00 E-03 0.87 E-03 □ Pass

Acidity < 3.00 E-02 2.00-5.8 E-02 ı. Borderline

Water content < 30 ppm Not measured -

Note: Breakdown voltage varies with number of prior breakdowns (experimental design)

III.10.3 AI Predictions vs. IEC Criteria

The AI system correctly identified: - 100% of oils meeting IEC 60296 as “NEUF” (new) - 80% of degraded oils as “needs monitoring/replacement” - Strong correlation between AI “condition” and measured breakdown voltage

III.11 Future Work and Improvements

III.11.1 Dataset Enhancement

Immediate Actions: 1. Collect 100+ additional samples for minority classes 2. Include oils from operational transformers (field data) 3. Document temperature effects on color 4. Test with different oil brands (Shell, Mobil, etc.).

III.11.2 Algorithm Improvements

Advanced ML Techniques: 1. Convolutional Neural Networks (CNN): - Direct image input (no manual feature extraction) - Potential for 5-10% accuracy improvement - Requires larger dataset (1000+ images)

2. Ensemble Methods:
   - Combine Random Forest + Gradient Boosting + SVM
   - Voting/stacking for robust predictions
3. Deep Learning for Regression:
   - ResNet/VGG architectures for flash count
   - ***Expected improvement: R^2 from 0.02 → 0.3-0.5***

III.11.3 System Integration

Hardware: - Custom photography box with controlled lighting - Smartphone app for field use

- IoT integration for remote monitoring

Software: - Web-based diagnostic portal - Automatic report generation (PDF) - Trend

analysis over time - Integration with SCADA systems

III.11.4 Multi-Modal Sensing

Proposed Enhancements: 1. UV-Vis Spectroscopy: Precise spectral analysis 2. Fluorescence Imaging: Detect aromatic compounds 3. Thermal Imaging: Temperature-dependent degradation 4. Combined Model: Image + DGA data fusion

III.11.5 Val idation Studies

Required Research: 1. Blind testing with 500+ unknown samples 2. Inter-laboratory comparison study 3. Long-term field trial (12-24 months) 4. Statistical validation of AI vs. chemical tests

III.12 Conclusions

This chapter has presented an integrated experimental and artificial intelligence-based study for the diagnosis of transformer insulating oil aging, combining standardized high-voltage breakdown testing with computer vision and machine learning techniques.

The experimental phase demonstrated measurable degradation trends across four oil categories — new Borak 22, new Nynas, in-service Borak 22, and out-of-service Borak 22 — with mean breakdown voltages declining from 20.67 kV for new oil to 14.10 kV for expired samples. Visual analysis confirmed a consistent relationship between increasing electrical stress and observable changes in oil color, turbidity, and carbon particle accumulation, providing a sound physical basis for image-based diagnostics.

A dataset of 218 standardized oil sample photographs was assembled and processed through a 23-feature computer vision pipeline, from which four machine learning models were trained using the Random Forest algorithm. The oil type classifier achieved an accuracy of 81.82%, while the oil condition classifier reached 90.91% overall accuracy, demonstrating the viability of image-based oil identification. Flash count regression yielded a mean absolute error of 2.02 flashes, with 60% of predictions falling within a ±2 flash tolerance, while flash category classification achieved 54.55% accuracy, with the highest performance observed for heavily degraded oil samples.

Feature importance analysis identified turbidity index, color channel ratios, and carbon detection metrics as the most diagnostically significant variables, aligning with the physical mechanisms of oil aging under repeated electrical breakdown.

The proposed diagnostic system offers several practical advantages — including assessment times under five seconds, non-destructive testing, and minimal infrastructure requirements — positioning it as a viable tool for preliminary field screening and condition-based maintenance planning. Its limitations, notably reduced performance on minority classes and flash count regression, are primarily attributable to the modest dataset size and class imbalance, and are expected to improve substantially with expanded data collection and the adoption of deep learning architectures.

Overall, this work establishes a proof of concept for rapid, image-based transformer oil diagnostics and opens promising avenues for integration with smartphone platforms, IoT-based monitoring systems, and multi-modal sensing frameworks in future research.

GENERAL CONCLUSION

GENERAL CONCLUSION

This thesis has presented a comprehensive and integrative investigation into the aging diagnosis of insulating oils in power transformers, combining theoretical foundations, a critical survey of diagnostic methodologies, experimental characterization under controlled high-voltage conditions, and the development of an artificial intelligence-based diagnostic system grounded in computer vision and machine learning.

Summary of Principal Findings

The review presented in Chapter I established the fundamental physicochemical and electrical properties that govern the behavior of transformer insulating oils, and identified the principal degradation mechanisms — oxidation, hydrolysis, thermal pyrolysis, and partial discharge activity — that progressively compromise oil quality under service conditions. It was shown that mineral oil, despite being susceptible to oxidative degradation and presenting inherent fire hazards, remains the dominant insulating medium in power transformers worldwide due to its favorable dielectric properties, thermal conductivity, and low cost. The joint degradation of oil and cellulosic insulation under the combined action of temperature, oxygen, and moisture was identified as the primary driver of transformer aging, underscoring the diagnostic value of physicochemical oil testing and dissolved gas analysis.

Chapter II demonstrated that the landscape of transformer oil diagnostic methods encompasses a rich spectrum of approaches, from standardized physicochemical tests and DGA-based ratio methods to sophisticated graphical representations and artificial intelligence frameworks. The comparative analysis of traditional ratio methods — Dornenburg, Rogers, and IEC 60599 — revealed their shared limitation of producing uninterpretable cases when gas ratios fall outside defined code combinations, motivating the adoption of more flexible, data-driven diagnostic strategies. The Duval Triangle and Pentagon methods, by virtue of their graphical completeness and expanded fault zone coverage, represent a significant improvement over ratio-based approaches. Nevertheless, the review of artificial intelligence techniques confirmed that machine learning and deep learning models — trained on sufficiently large and representative datasets — are capable of achieving diagnostic accuracies that surpass those of any single conventional method, while simultaneously processing multidimensional feature vectors that no human expert could efficiently interpret in real time.

The experimental investigation reported in Chapter III produced a series of findings of both scientific and practical significance. Breakdown voltage measurements performed in strict compliance with IEC 60156 on four oil categories — new Borak 22, new Nynas, in-service Borak 22, and out-of-service Borak 22 — confirmed a consistent and statistically meaningful decline in dielectric strength with advancing oil degradation. New Borak 22 oil exhibited the highest mean breakdown voltage of 20.67 kV, followed by new Nynas at 17.49 kV, in-service Borak 22 at 15.43 kV, and expired Borak 22 at 14.10 kV. These measurements, while obtained under laboratory conditions involving accelerated electrical stress rather than long-term thermal aging, provided clear empirical validation of the expected degradation trajectory and established the ground truth for subsequent machine learning model training.

Visual analysis of the 218 standardized oil sample photographs revealed systematic relationships between increasing electrical breakdown events and observable changes in oil color, turbidity, and carbon particle accumulation. The extracted feature set of 23 color and visual indices — spanning the RGB, HSV, and LAB color spaces alongside custom diagnostic indices — captured these degradation signatures with sufficient discriminative power to support automated classification. Feature importance analysis identified the turbidity index as the strongest single predictor of oil condition, accounting for 14.86% of the Random Forest model's decision weight, followed by color channel ratios and the carbon particle detection metric. These findings are consistent with the known physical mechanisms of oil aging: carbon deposits from electrical arcing increase light scattering and shift the spectral balance of transmitted light, while oxidation products and sludge formation alter the colorimetric response of the oil.

The four machine learning models trained on this dataset achieved differentiated but collectively informative performance levels. The oil condition classifier attained the highest overall accuracy of 90.91%, demonstrating strong capability in distinguishing new oil from degraded samples. The oil type classifier achieved 81.82% accuracy in discriminating between Borak 22 and Nynas oils based solely on visual features. The flash category classifier reached 54.55% accuracy, with substantially better performance on the heavily degraded category, reflecting the more pronounced and visually distinct degradation signatures associated with high numbers of electrical breakdowns. Flash count regression yielded a mean absolute error of 2.02 discharges, with 60% of predictions falling within a tolerance of ±2 flashes — an accuracy level considered acceptable for the purposes of preliminary field screening, though insufficient for precise quantitative estimation of cumulative electrical stress.

Contributions and Limitations

The principal contribution of this work lies in the demonstration that photographic image analysis, combined with an appropriately designed computer vision feature extraction pipeline and a Random Forest classification framework, constitutes a viable approach for rapid, non-destructive preliminary assessment of transformer oil health. The proposed diagnostic system operates in under five seconds per sample, requires no chemical reagents, and is deployable using commercially available camera hardware and standard computing equipment. Its integration as a preliminary screening tool — directing maintenance resources toward units requiring immediate detailed chemical testing — represents a cost-effective complement to established laboratory methods.

Several limitations of the present work must be acknowledged. The dataset of 218 samples, while sufficient to establish proof of concept, is modest by the standards required for the robust training of high-accuracy classifiers, particularly for the minority classes of in-service and out-of-service oil, which comprised only 19 and 6 samples respectively. The severe class imbalance observed in the condition classification task limited the recall performance for degraded oil categories and introduced an inherent bias toward the majority new-oil class. Furthermore, the experimental conditions — involving controlled laboratory breakdown testing on small oil samples rather than in-situ aging of operational transformer oil — represent a simplified proxy for the complex, multi-mechanism degradation that occurs over years of field service. The generalizability of the trained models to oils from other manufacturers, transformer designs, or operating environments remains to be validated.

Recommendations and Future Perspectives

Building upon the foundations established in this work, several directions for future research are recommended. In the near term, the most impactful improvement would be the systematic expansion of the training dataset to include a minimum of 100 samples per condition category, incorporating oils sampled from operational transformers at varying stages of service life, and encompassing a broader range of oil types and brands. Parallel efforts to address class imbalance through synthetic data augmentation techniques — including Generative Adversarial Networks (GANs) and advanced oversampling strategies — would further enhance model robustness.

From an algorithmic perspective, the application of Convolutional Neural Networks (CNNs) directly to the raw image data, bypassing the manual feature engineering stage, represents the most promising avenue for accuracy improvement. CNN architectures such as ResNet or EfficientNet, pre-trained on large image datasets and fine-tuned on the oil sample domain, are expected to uncover higher-order spatial and textural features that are not captured by the channel-mean and ratio-based features employed in the present study. The integration of image-based diagnosis with dissolved gas concentration data in a multimodal fusion framework would further enrich the diagnostic information available to the model, potentially enabling fault type identification — not merely condition assessment — from field measurements alone.

In terms of deployment, the development of a smartphone-based application incorporating a standardized photography guide, automatic image quality assessment, and on-device inference would substantially lower the barrier to adoption in field environments. Integration with supervisory control and data acquisition (SCADA) systems and IoT-based transformer monitoring platforms would enable continuous, automated tracking of oil condition trends over time, supporting the transition from periodic inspection-based maintenance to truly condition-based and predictive asset management strategies.

Closing Remarks

Power transformer reliability is not merely a technical objective — it is a prerequisite for the social and economic continuity of modern societies. As electrical networks age, as the penetration of renewable energy sources imposes new operational stresses on transformer assets, and as the complexity and cost of transformer replacement escalates, the imperative for intelligent, data-driven condition monitoring has never been greater. The work presented in this thesis, while necessarily limited in scope, aspires to contribute a small but substantive step toward the realization of that imperative: demonstrating that the confluence of experimental rigor, standardized data acquisition, and modern machine learning can yield diagnostic tools that are both scientifically sound and practically deployable in the service of safer, more reliable electrical infrastructure.

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