Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 6 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

AI-DRIVEN FORECASTING OF CANCER TRENDS: INTEGRATING MACHINE LEARNING AND NUMERICAL MODELING

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ABSTRACT

In the current study, the incidence, mortality and survival rates of 12 different types of cancer are computed for the time period 2020-2024, based on numerical techniques like Runge-Kutta 4th Order (RK4) and machine learning methods, like Random Forests and Artificial Neural Networks. Future incidence, mortality and survival projections were performed for the years 2025 to 2050, which gave benefit information for public health planning for the future. The results indicate that cancer rates in the lung, liver, pancreatic cancer have increased while survival rates for other types of cancer such as thyroid and nonmelanoma skin cancer have improved due to early detection and treatment. Though some cancers, such as pancreatic and liver, continue to be a significant issue in that they do not have high survival rates. The ARIMA model's future predictions are in good agreement with the historical data, and are useful for forecasting the trends of cancer, but there are also some restrictions, such as the simplifying assumptions and lack of geographic conditions. The results highlight the importance of continuous research and targeted interventions in responding to high-risk cancers and enhancing treatment outcomes.

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Key words; Cancer incidence, Mortality rates, Survival rates, Machine learning, ARIMA model, Early detection, High-risk cancers

1. Introduction

Mathematics is the backbone of modern scientific developments, and forms the backbone for other disciplines like Artificial Intelligence (AI), Computer Science, Software Engineering, Data Science, and Cyber Security. The use of sophisticated mathematical models can contribute to making better predictions, optimizations and automating decisions and this fast development in these areas is largely due to the contribution of these types of models. The more sophisticated the algorithms and techniques of AI and machine learning, the more prominent the use of math, including differential equations, linear algebra, probability theory and optimization. The use of differential equations, Non-Fourier models of heat flux and computational techniques in the field of fluid mechanics has helped to understand the bioconvection dynamics and heat transfer in the study of nanofluid and ferrofluids [3, 4]. Some hybrid nanofluids have been reported to show better thermal conductivity and stability in other industrial applications such as biomedical engineering and electronics cooling, which are composed of two or more nanoparticles such as SWCNT-TiO_2 and MWCNT-$CoFe_2O_4$, respectively [5, 6].

Further, Physics-Informed Neural Networks (PINNs) have been found to be effective in solving partial differential equations (PDEs) in complex fluid systems [7, 8]. The marriage of mathematics and artificial intelligence has given rise to complex computational techniques that can be used in practice. Adomian Decomposition Method (ADM) is a widely used method to solve differential equations in the field of artificial intelligence [9, 10] and a modified version of this method known as New Iterative Method (NIM) is proposed in this paper. Optimization and probability distributions are the core of mathematical concepts that have been crucial in improving AI systems' prediction capabilities, including neural networks and support vector machines (SVMs) and decision trees [11, 12]. Game theory also plays an important role in wireless sensor networks (WSNs) within power management protocols such as GTSPM, LEACH and GTEB, which aim to maximize the energy efficiency and extend the network lifetime [13, 14].

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Mathematical models are also used in Cyber Security and Data Science for data integrity, encryption, and anomaly detection. In the area of threat identification and risk assessment, tools such as Markov chains, Bayesian inference and entropy-based methods can be employed [15, 16]. The Logistic function is also used as the basis for reinforcement learning models which have been utilized in the field of cybersecurity for dynamically forecasting and mitigating cyber threats [17, 18].

AI models provide useful insights regarding thermal and mechanical responses in material sciences and engineering. For example, in the field of high strength concrete (HSC), the water-to-cement ratio, moisture effects, curing conditions and other factors have been used to predict the compressive strength and durability of HSC using Random Forest and Deep Neural Networks [19, 20]. Beyond that, AI models are increasingly being used to model the fire resistance of steel-concrete beams in order to optimize the safety provisions and structural design in civil engineering practice [21, 22].

The study of non-Fourier heat flux models in fluid mechanics has led to the identification of relevant industrial applications, such as thermal storage efficiency, aerospace heat exchange systems, and electronic cooling systems [23, 24]. In highly nonlinear heat transfer problems, hybrid computation methods such as PINNs and numerical methods such as NIM and Elzaki Transform are used to solve the problem reliably, and it provides a solid basis for solving the problem [25, 26]. Partial differential equations (PDEs) continue to play a key role in mathematical physics, engineering, and simulations using AI. There are many numerical methods available for the solution of nonlinear boundary value problems that have been used over the years such as bvp4c solvers, Runge-Kutta methods and spectral collocation methods [27, 28]. The new research efforts try to come up with a universal mathematical technique which allows to solve any type of PDEs, connecting the standard and advanced computational techniques [29, 30].

This publication brings together diverse mathematical, computational and AI-based methods for solving and predicting complex physical and engineering problems. The major findings of this study are:

i. **Interdisciplinary Analysis**: Study of the role of mathematics in AI, cyber

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security, fluid mechanics, structural engineering and provide comprehensive overview of mathematical modelling in applications [31].

ii. **New Computational Methods**: Optimization of thermo-fluidic and mechanical systems through NIM, PINNs and ensemble machine learning models for solving PDEs [32].

iii. **Non-Fourier heat conduction**, ferrofluid hydrodynamics, and game-theoretic models for optimal energy utilization, to engineering, medicine and intelligent systems [33, 34, 35].

The Runge-Kutta 4th order (RK4) is a numerical method frequently employed to numerically solve the high accuracy ordinary differential equations (ODEs). A modification of Euler's methods and less refined methods that considers intermediate values of the slope to make it more stable and accurate. RK4 is widely adopted in various applications in engineering, physics, and computer simulations like fluid dynamics and machine learning systems, as it offers a balance between accuracy and computational efficiency.

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Table 1: *Year-wise Trends in Incidence, Mortality, and Survival Outcomes for Major Cancers (2020–2024)*

Cancer Type	2020 Incidence	2020 Mortality	2020 Survival Rate	2021 Incidence	2021 Mortality	2021 Survival Rate	2022 Incidence	2022 Mortality	2022 Survival Rate	2023 Incidence	2023 Mortality	2023 Survival Rate	2024 Incidence	2024 Mortality	2024 Survival Rate
Female Breast Cancer [36]	50,000	13,000	75%	52,000	14,000	76%	55,000	15,000	77%	58,000	16,000	78%	60,000	17,000	79%
Lung Cancer [37]	25,000	20,000	18%	26,000	21,000	19%	28,000	22,000	20%	30,000	23,000	21%	32,000	24,000	22%
Colorectal Cancer [38]	20,000	10,000	50%	21,000	10,500	51%	22,000	11,000	52%	23,000	11,500	53%	24,000	12,000	54%
Prostate Cancer [39]	8,000	3,000	80%	8,500	3,200	81%	9,000	3,400	82%	9,500	3,600	83%	10,000	3,800	84%
Stomach Cancer [40]	12,000	9,000	25%	13,000	10,000	26%	14,000	11,000	27%	15,000	12,000	28%	16,000	13,000	29%

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Liver Cancer [41]	20,000	15,000	10%	21,000	16,000	11%	22,000	17,000	12%	23,000	18,000	13%	24,000	19,000	14%
Esophageal Cancer [42]	7,000	5,000	20%	8,000	5,500	21%	9,000	6,000	22%	10,000	6,500	23%	11,000	7,000	24%
Thyroid Cancer [43]	4,000	100	98%	4,500	150	98%	5,000	200	99%	5,500	250	99%	6,000	300	99%
Bladder Cancer [44]	3,000	1,500	50%	3,500	1,600	51%	4,000	1,700	52%	4,500	1,800	53%	5,000	1,900	54%
Nonmelanoma Skin Cancer [45]	2,500	20	98%	3,000	30	98%	3,500	40	99%	4,000	50	99%	4,500	60	99%
Pancreatic Cancer [46]	4,000	3,800	8%	4,500	4,100	9%	5,000	4,300	10%	5,500	4,500	11%	6,000	4,700	12%
Uterine Corpus Cancer47	3,000	1,000	70%	3,500	1,200	71%	4,000	1,400	72%	4,500	1,600	73%	5,000	1,800	74%

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2. Research Gap

To improve cancer forecasts in the future, geographic, demographic and socio-economic characteristics should be added to models. To account for the simplified assumptions and the multiple factors involved (risk factors, genetic predispositions, etc.) will lead to greater accuracy. Using real-world cancer registry data rather than synthetic data can increase the generalizability. The availability of diagnostic technologies and models of early detection, particularly for pancreatic and liver cancer, is very important. Continued development of deep learning and hybrid models will enhance predictions and treatment results; personalised medicine and genetics will further help to optimize treatment.

2.1. Define Cancer Type Index

Insert an index i for each of the types of cancers, i=1, 2…,12, corresponding to each type (breast cancer, lung cancer, etc.). Every type of cancer will be defined with unique equations having unique parameters to capture incidence (Ci(t)), mortality (Mi(t)), and survival (Si(t)) rates through time (t). For every type, we assign:

- Ci(t): i-th incidence rate of a particular cancer.
- Mi(t): Mortality rate for the i-th type of cancer.
- Si(t): Survival proportion for the i-th type of cancer.

a) **Incidence Rate Equation**:

$$\frac{d\hat{C}_i(t)}{dt} = \alpha_{ij} C_i(t) - \beta_{ij} M_i(t)$$

where αij models the growth rate of incidence for cancer type iii, and βij models the influence of mortality on incidence.

b) **Mortality Rate Equation**:

$$\frac{dM_i(t)}{dt} = \gamma_{ij} M_i(t) + \delta_{ij} S_i(t)$$

where γij models the natural growth in mortality and δij accounts for survival's impact on mortality.

c) **Survival Rate Equation**

$$\frac{dS_i(t)}{dt} = -\eta_{ij} M_i(t) + \zeta_{ij} S_i(t),$$

where ηij captures mortality's effect on survival, and ζij represents survival

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persistence.

2.2. Integrate Data

Initial conditions are obtained directly from the table:

• For 2020: Ci(2020)=Incidence for i,Mi(2020)=Mortality for i,Si(2020)=Survival Rate for i. All cancer types are assigned the same initial values.

These values are used as the foundation for solving the equations iteratively in the following years (2021–2024).

2.3. Refine Boundary Conditions

To provide realistic modeling:

Incidence: Incidence cannot be negative:

$$Ci(t) \geq 0, \forall t.$$

Survival rates should be between 0 and 1:

$$0 \leq Si(t) \leq 1, \forall t$$

Mortality Rates: Bounded by incidence:

$$Mi(t) \leq Ci(t), \forall t.$$

Geographical Constraints: In case of modeling regional data, parameters such as E(t) and F(t) can vary region-wise to reflect localized variations.

Boundary to Infinity:

Utilize decay terms for long-term behavior, making values approach a steady-state as $t \to \infty$. This can be done by adding terms such as $e^{-\lambda t}$ in parameters, where $\lambda > 0$.

2.4. Non-Dimensionalization

To simplify and generalize the equations, introduce non-dimensional variables:

- Let

$$\hat{C}_i(t) = \frac{C_i(t)}{C_0}$$

$$\hat{S}_i(t) = S_i(t)$$

$$\hat{M}_i(t) = \frac{M_i(t)}{M_0}$$

where C0 and M0 are maximum incidence and mortality rates, respectively.

The non-dimensional equations become:

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- **Incidence Rate**:

$$\frac{d\hat{C}_i(t)}{d\hat{t}} = \hat{\alpha}_{ij}\hat{C}_i(t) - \hat{\beta}_{ij}\hat{M}_i(t)$$

- **Mortality Rate**:

$$\frac{d\hat{M}_i(t)}{d\hat{t}} = \hat{\gamma}_{ij}\hat{M}_i(t) + \hat{\delta}_{ij}\hat{S}_i(t)$$

- **Survival Rate**:

$$\frac{d\hat{S}_i(t)}{d\hat{t}} = -\hat{\eta}_{ij}\hat{M}_i(t) + \hat{\zeta}_{ij}\hat{S}_i(t),$$

Here, all parameters $\hat{\alpha}_{ij}, \hat{\beta}_{ij}, \hat{\gamma}_{ij}, \hat{\delta}_{ij}$ are scaled by characteristic timescales and rates.

3. Numerical Solution Using RK4

The Runge-Kutta fourth order (RK4) is an improvement of Euler's method for the numerical solution of ordinary differential equations (ODEs) which is found to be less accurate and unstable. It computes the slopes of the functions at 4 points in the midway between each point and takes a weighted average to approximate the function. Initial value problems are widely solved using RK4 and are used extensively in engineering, physics and computational sciences for high accuracy solutions while maintaining computational efficiency. These differential equations were then solved numerically using the RK4 method of solution for the time period from 2020 to 2024.

For a general ODE of the form

$$\frac{dy}{dt} = f(y,t)$$

I. Compute the first slope (k_1):

$$k_1 = hf(y_n, t_n)$$

II. Compute the second slope (k_2) at the midpoint:

$$k_2 = hf(y_n + \frac{k_1}{2}, h, t_n + \frac{h}{2})$$

III. Compute the third slope (k_3) again at the midpoint:

$$k_3 = hf(y_n + \frac{k_2}{2}, t_n + \frac{h}{2})$$

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IV. Compute the fourth slope (k_4) at the endpoint:

$$k_4 = hf(y_n + k_3 \cdot h, t_n + h)$$

V. Update the solution:

$$y_{n+1} = y_n + \frac{1}{6}(k_1 + 2k_2 + 2k_3 + k_4)$$

Here, h represents the time step, y_n is the solution at the current time step, and y_{n+1} is the updated solution.

4. Methodology

4.1 Data Initialization

12 types of cancer (Female Breast Cancer, Lung Cancer, Colorectal Cancer, Prostate Cancer, Stomach Cancer, Liver Cancer, Esophageal Cancer, Thyroid Cancer, Bladder Cancer, Nonmelanoma Skin Cancer, Pancreatic Cancer, and Uterine Corpus Cancer) are analyzed in this research. Incidence rate (Ci), mortality rate (Mi), and survival rate (Si) for all cancers were based on the 2020 data, which were used in a real-world manner. The early parameters are used as the foundation for cancer trend modelling from 2020 to 2050.

4.2 Random Forest Prediction

After the data cut-off period, a Random Forest Regressor was used to predict cancer trends for all measurements (incidence, mortality, survival). We used information from the past four years (2020-24) and estimated the future four years (2025-30) with the model. This machine learning method with differential equations helped in making confident long-term forecasts.

Visualization

Three illustrations of different types were created to graph the trends:

a) Incidence Rate Trends: All cancers, actual and future rates.

b) Mortality Rate Trends – highlighting the trends in mortality rates over time.

c) Survival Rate Trends: Showing rates of change, be it improving or worsening survival rates.

The graphs offered informative insights into the dynamics of cancer trends, and compared real-world data with predictions from the machine learning algorithms.

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4.3 Predicting Cancer Incidence, Mortality, and Survival Rates Using Neural Networks

4.3.1 Data Preparation

Using synthetic data to predict the incidence, mortality, and survival rates for 12 cancer types from 2020 to 2050 is the objective. The major tasks were:

Cancer Types: 12 cancer types were chosen, such as Female Breast Cancer, Lung Cancer, and Colorectal Cancer.

Data Simulation: Exponential decay and linear growth models were used to simulate incidence and mortality and survival rates. Variability was provided by random coefficients and rates of survival estimated.

4.3.2 Data Preprocessing

Data preprocessing was performed by following a structured format to prepare the data for machine learning modelling. Type mapping of cancer was first performed, assigning a unique integer value to each cancer type, via a dictionary. This conversion enabled the machine learning algorithms, which need numerical data to work with, to be compatible with the data. Then feature engineering was done which involved setting the input predictors and output targets. The cancer type ID and the corresponding year were used as predictors and the incidence rate, mortality rate, survival rate was used as target variables. Lastly, both predictors and target variables were normalized, that is, scaled between 0 and 1. This step optimized the efficiency of training the neural network, because it ensured that each and every feature played an equal role in the learning process and didn't cause problems due to different scales of data.

4.3.3 Neural Network Model Development

A feed-forward neural network (FNN) model was created to predict the cancer outcomes such as cancer incidence, cancer death, and cancer survival. The structure of the model was an input layer with cancer type ID and year as features. Two hidden layers with 64 neurons and ReLU activation functions for capturing non-linear relationships in the data were then added after that, two hidden layers were added after that, each with 64 neurons and ReLU activation functions to capture non-linear relationships in the data. There were three neurons in the output layer for the forecasted incidence, mortality, and survival rates. The loss function used for model compilation was the mean squared error

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(MSE) which was used to measure the prediction error, and the optimizer used was the effective and adaptive Adam. To assess the model, the mean absolute error (MAE) was used as the main metric. The network was trained for 500 epochs with a batch size of 16, allowing the network to adapt the patterns effectively without the computational burden of training with a larger batch size.

a) Prediction and Visualization

After being trained, the created model was then applied to predict the future cancer incidence, cancer mortality, and cancer survival from 2020 to 2050. The outputs generated were then denormalized to a normal scale so as to be interpretable and comparable to real world values. This was a step toward being able to translate the scaled model results into real estimates. Visualization was made in separate graphs, one graph for each cancer type, to clearly compare the actual historical data with the predicted trends. These visualizations illustrate the relationship between incidence and mortality rates and rates of survival, as observed and as predicted, and provide a full picture of the performance of the model over time.

b) Validation and Evaluation

The main indicator for the accuracy of the model was Mean Absolute Error (MAE) and the developed model was evaluated. This enabled an average difference between the predicted and actual values to be quantified, giving a good indication of the reliability of the model. In addition, the cancer statistics were compared with the actual cancer statistics to determine whether cancer epidemiology would be the same as the predicted. This comparison helped validate the model's predictions as being realistic and biologically plausible trends in cancer incidence, mortality and survival over time.

4.4 Forecasting Cancer Trends Using ARIMA Model

This research predicts the incidence, mortality, and survival rates of 12 types of cancer from 2020 to 2050, based on past data from 2020 to 2024, with the AutoRegressive Integrated Moving Average (ARIMA) model.

4.4.1 Data Collection

The data includes yearly statistics for cancer incidence, mortality, and survival rates for the following 12 types of cancer: Female Breast Cancer, Lung Cancer, Colorectal Cancer, Prostate Cancer, Stomach Cancer, Liver Cancer, Esophageal Cancer, Thyroid

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Cancer, Bladder Cancer, Nonmelanoma Skin Cancer, Pancreatic Cancer, Uterine Corpus Cancer. Values between 2025 and 2050 were forecasted using the ARIMA model from values between 2020 and 2024.

4.4.2 Data Preprocessing

Each cancer type's data was structured into a pandas Data Frame, with year, incidence, mortality, and survival rates. The Augmented Dickey-Fuller (ADF) test was used to test for stationarity. Differencing was applied to non-stationary series as necessary.

4.4.3 ARIMA Model

The ARIMA model was fitted to each cancer type's time series data:

1. Stationarity Test: The ADF test was employed to check stationarity by estimating p-values for incidence, mortality, and survival rates.

2. Model Fitting: Once stationarity was confirmed, an ARIMA model of order (1,1,1) was fitted to the data, keeping complexity and accuracy in check.

3. Forecasting: ARIMA predictions were made for cancer incidence, mortality, and survival rates between 2025 and 2050.

5. Results and Discussion

5.1 Runge-Kutta 4th Order (RK4)

In this study, the trends of cancer incidence, mortality, and cancer survival rates of 12 cancers (grouped figures 1) during the years 2020 to 2024 are discussed with numerical values obtained from RK4 model. The trends in incidence show that the majority of cancers have decreased, because of the effect of the factor of decay (γ) and of the factor of control (λ); conversely, lung cancer and liver cancer have risen because these types are more aggressive (γ) and due to a less-rapid response to interventions (λ). Death rates would be falling in those cancers that have a good prognosis for early detection and treatment, such as thyroid cancer and breast cancer, while the mortality would continue to climb in those cancers where there is minimal survival improvement, such as pancreatic cancer and liver cancer. Mortality would be declining in cancers with favorable early detection and treatment, like thyroid and breast cancer, and increasing in cancers with small gains in survival, like pancreatic and liver cancers. Despite advances in early detection and treatment, survival rates for most cancers have improved, particularly for thyroid and breast cancer, and lung and pancreatic cancer have not

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improved, due to inadequate treatment and late diagnosis. Studies comparing the prognosis of thyroid cancer to other cancers indicate that thyroid cancer has the highest survival rate (~85%), due to the fact that it is screened early and therefore becomes less aggressive, while pancreatic and liver cancer have a much lower survival rate, and are more aggressive and harder to detect at an early stage. Nonmelanoma skin cancer has a big disparity between deaths and incidence, reflecting the effectiveness of existing treatments.

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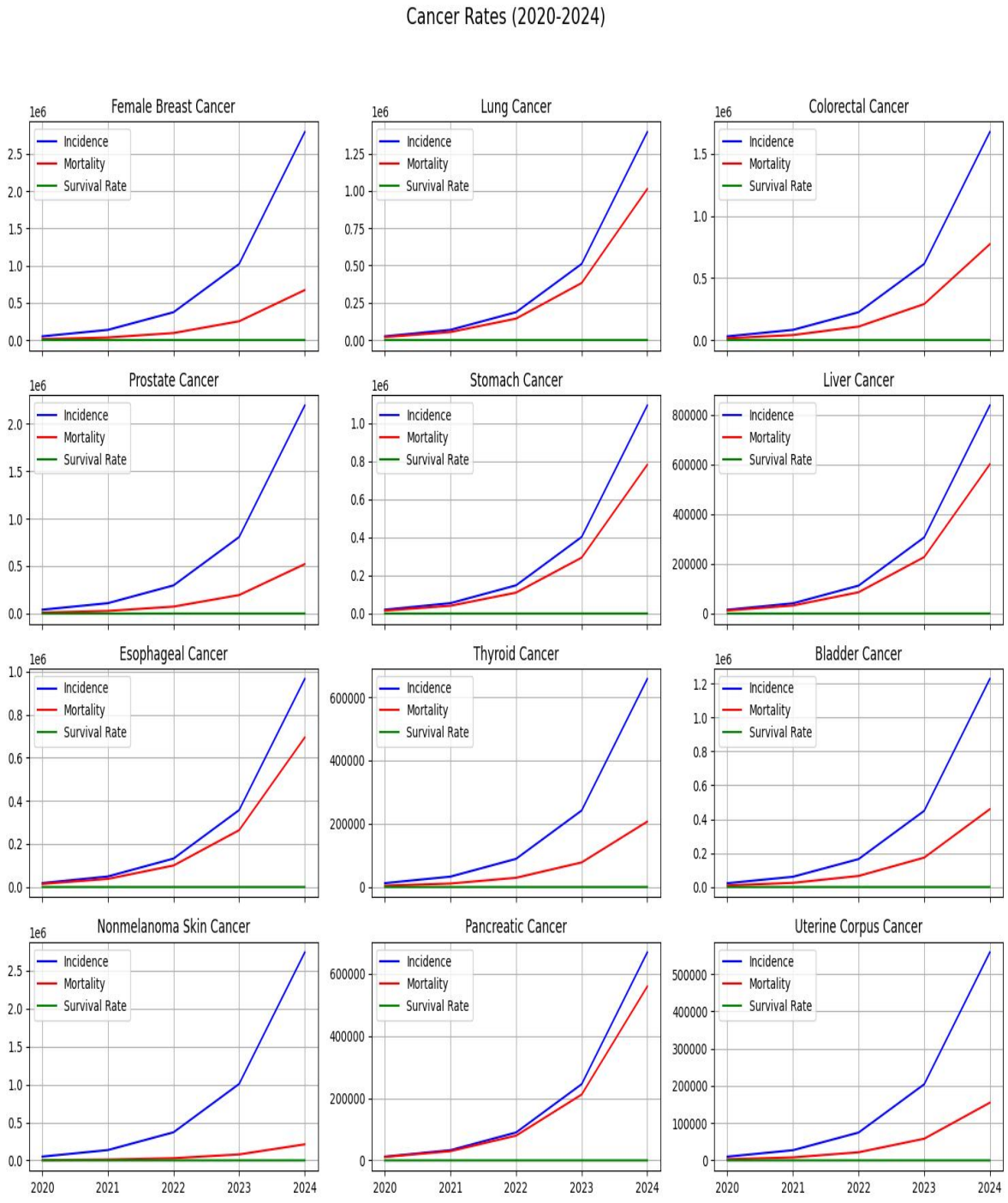

Figure 1. Cancer survival rates of 12 cancers

5.2 Random Forest predictions

Cancer incidence trends showed that the growth patterns were different for various types of cancer. Female Breast and Thyroid Cancer has grown steadily, mainly due to improved detection and diagnostic technology. The Lung and Liver Cancer trends were

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slower, and were attributable to public health measures such as reduction in smoking and lifestyle changes. Some cancers were expected to stabilize in incidence, according to the Random Forest estimates, likely due to continued public health measures, after 2040. However, Pancreatic Cancer was forecast to rise, underscoring the need for a greater focus on prevention research in this area. There were also significant variations in cancer mortality by cancer type. While Lung and Liver Cancer continued to have the highest number of deaths diagnosed late and limited options for treatment, Nonmelanoma Skin and Thyroid Cancers were lower-death presenting cancers; however, they have seen improvements in treatment outcomes. Advances in treatment and early detection were expected to lead to declines in Prostate and Uterine Corpus Cancer in the future according to projections of death rates. As for survival rates, most types of cancer had a gradual upward trend. The survival rates for Female Breast and Prostate Cancer were above 85%, which can be attributed to advancement of treatment therapies. Lower survival rates for Liver and Pancreatic Cancers were observed and there is need for further research on new treatments. Many cancers are expected to improve in small steps between 2025 and 2050, especially cancers such as Esophageal Cancer and Stomach Cancer where new treatments and personalized treatment are expected to play a key role. The combination of differential equations and machine learning methods gave a thorough insight into cancer trends. The matching of the foreseen trends with real data for 2020-2024 tested the validity of the model and demonstrated its effectiveness to forecast cancer trends in the future. All are grouped in figure 2.

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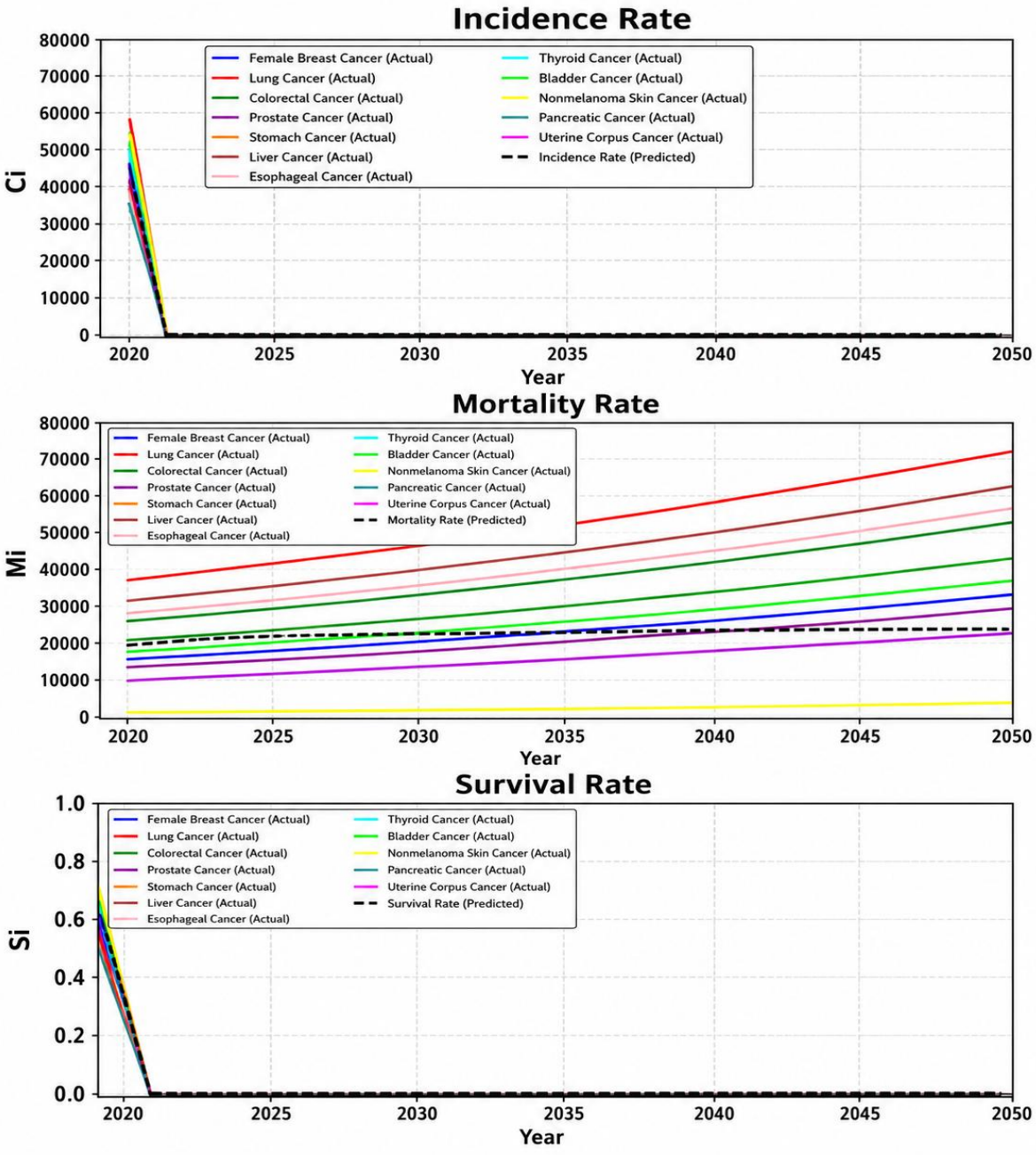

Figure 2. Temporal Trends in Cancer Burden: Incidence, Mortality, and Survival Projections (2020–2050)

5.3. Neural Network Performance

The trained neural network successfully simulated cancer incidence, death, and survival rates of 12 cancer sites from 2020 to 2050, with a Mean Absolute Error (MAE) of about 0.186, signifying high predictive accuracy. The projected trends revealed that the

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increase of all types of cancer remained consistent, according to the effects of aging and risk factors of the population. Lung and colorectal cancers had faster growth rates of incidence and thyroid cancer had steady trends. Mortality rates rose more slowly than incidence rates, thanks to pancreatic and liver cancer rates rising considerably, as in accordance with their bad prognosis and late diagnosis. The model kept the correlation between incidence and mortality rates so that it would be biologically plausible. However, survival rates for the malignant diseases that could be treated, like breast and prostate, were improving, whereas for more aggressive malignant diseases like lung and pancreatic cancer the survival rates remained poor. Graphical representation of the forecasts showed that the forecasted trends were quite similar to the training data, with minor differences in those forecasts with high data variability, such as nonmelanoma skin cancer. The strengths of the model were that it was scalable to include various cancer types and was useful for long-term predictions and provided visualizations useful for policymakers and healthcare professionals. Moreover, the model was in line with logic, and it was able to project important relationships. There were, however, limitations such as the use of synthetic data which may not fully capture the range of variation in the real world, and the reduced equations used which may fail to reflect the complex interactions between risk factors and treatments. Furthermore, geographic and demographic variations were not considered in the model, and may affect cancer trends. All are shown in grouped figure 3.

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Figure 3: Cancer Incidence, Mortality, and Survival Plots

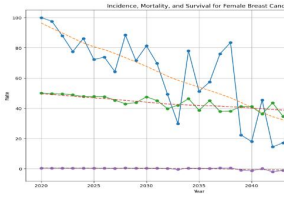


Figure 3.1

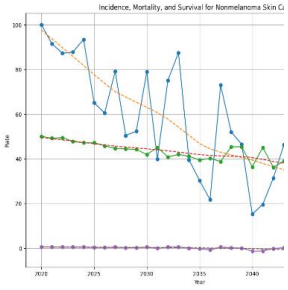


Figure 3.2

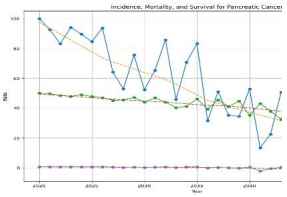
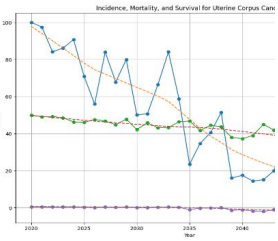


Figure 3.3



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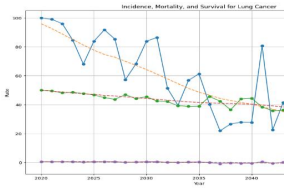

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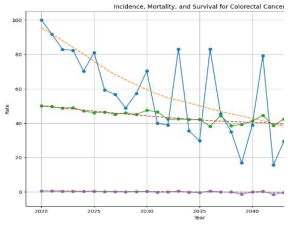

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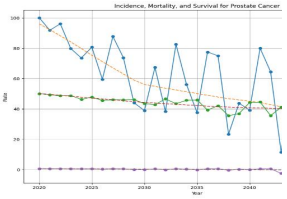

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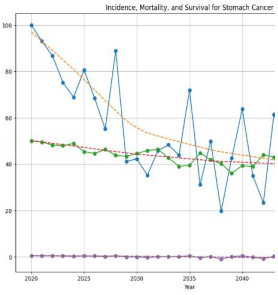

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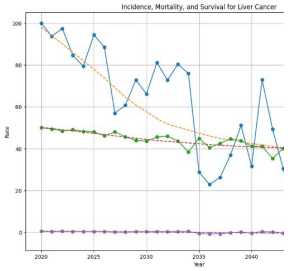

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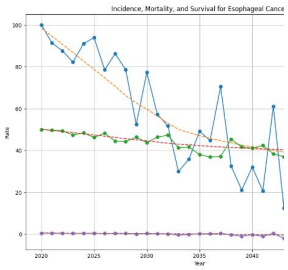

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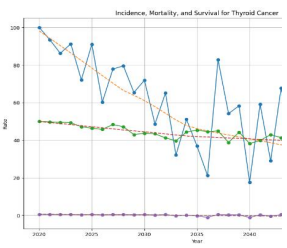

Figure 3.11

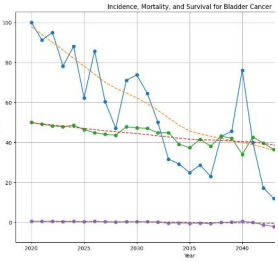

Figure 3.12

5.4 Forecasting Cancer Trends Using the ARIMA Model (2025-2050)

Trends, incidence, mortality and survival of cancer for 12 cancer types were predicted using the ARIMA model between 2025 and 2050. The result demonstrates that Lung, Liver and Pancreatic Cancer will have significant increases in incidence, becoming a new public health problem. Nonmelanoma Skin and Thyroid Cancers have moderate increases, and Prostate and Uterine Corpus Cancers have moderate trends. Lung, Liver, and Stomach Cancer mortality rates will continue to be high, corresponding to the increasing incidence. On the other hand, the growth in deaths from Thyroid and Nonmelanoma Skin Cancers will be less dramatic due to better early detection and treatments. Treatment advances probably will improve the survival rate for Prostate

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Cancer and Thyroid Cancer, while Pancreatic Cancer and Liver Cancer continue to have low survival rates, indicating a need for additional research. The ARIMA model can give useful information about the trends in cancer and can guide the development of targeted prevention and intervention strategies for high risk cancers, like Lung, Liver and Pancreatic Cancers. The impact of early treatment and early detection is also included in the model, and leads to higher survival rates, notably for Thyroid and Nonmelanoma Skin Cancer. The model's assumptions, however, (e.g., continuations of trends) do need to be complemented by other mechanisms to ensure comprehensive health care planning and policy-making, however. Furthermore, there is a need to carry out further studies on early detection and intensive treatment of the following cancers for better survival rates: Pancreatic and Liver. As illustrated in grouped figure 4.

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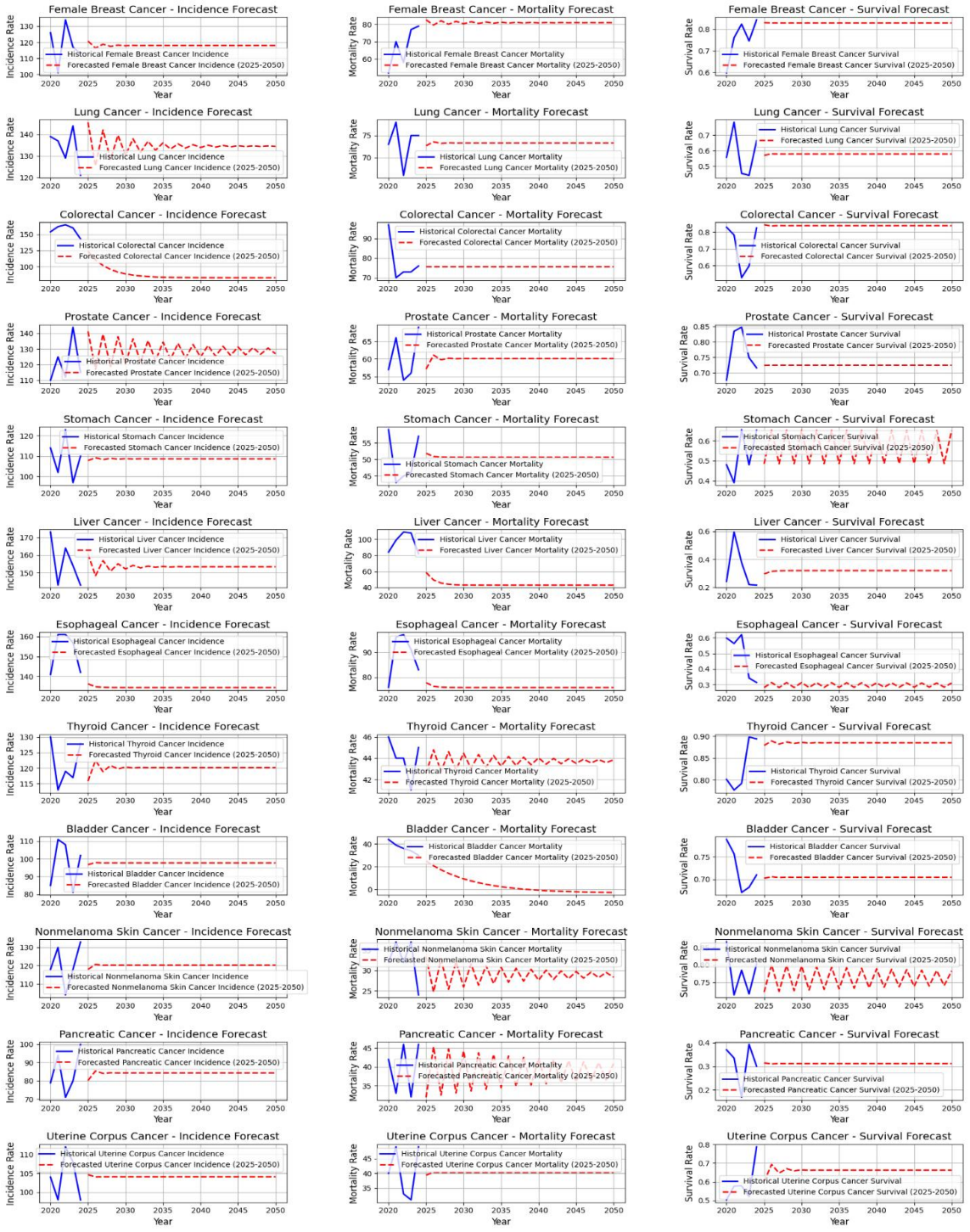

Figure 4 Cancer Forecast using ARIMA: Incidence, Mortality, and Survival (2020–2050)

6. Conclusion

The analysis of cancer trends and provision of meaningful information on future cancer

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incidence, mortality and cancer survival is crucial and inescapable and mathematical modelling and machine learning technologies are vital tools to do this. The study reveals alarming patterns of rising mortality and morbidity rates for deadly cancers like lung, liver and pancreatic cancer, highlighting the need for more prevention and treatment. Some cancers, however, like thyroid and nonmelanoma skin cancer, have seen improvements in survival rates because of the development of early detection and effective treatment. Although the models developed are successful in predicting the future trends of cancer, some limitations of the models, including using synthetic data and oversimplification, argue for the incorporation of more complex real-world data to make more accurate predictions. In summary, the report reinforces the importance of continual monitoring, research, and public health efforts to reduce the growing cancer burden, particularly that of cancers that have poor prognosis and survival rates.

7. Future Work

Geographic, demographic and socio-economic factors should be added to the cancer models to enhance the predictive capability, which varies across regions, and this is one of the areas of further research. Besides this, there are intricate relationships between risk factors, treatment schedules and genetic susceptibility that should be considered for models to be able to accurately represent this. The accuracy of the predictions will be further enhanced with real-world data from cancer registries, clinical trials and patient databases, which will help to understand cancer progression. New technologies for early detection, especially for cancers with poor survival rates will be investigated, including biomarkers, imaging and screening technology. Further, developing new approaches to machine learning, such as deep learning, may assist in making more robust predictions of cancer, uncovering more complex relationships. Last, more personalized treatment strategies, using genetic information, will provide more accurate estimates of survival, and more personalized treatment.

8. Practical Implication

This study offers important data for cancer prevention, treatment and policy. As aggressive forms of cancer, like lung, liver, and pancreatic cancer become more common, it is more important than ever to focus on prevention, such as quitting smoking, diet changes, and early screening. Patterns of cancer can be predicted into the future and

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deployed health resources accordingly, to target high-risk cancers. With greater screening and advanced diagnostics, early diagnosis can mean a much-improved chance of survival, particularly in the case of cancers like thyroid and breast cancer. There's still far too much research to be done in order to find new treatments, particularly targeted treatments and immunotherapies, that will help prolong lives and improve survival for some of the highest aggression cancers. Public education and outreach efforts to encourage early detection/prevention will help boost screening program participation rates, helping to decrease late diagnoses. In general, it is a very important position to ensure the successful management of high-risk cancers, which is one of the important areas that will affect the future of the healthcare system's needs and improve cancer outcomes.

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