Arkangel Ai

AI use cases for HealthCare

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Arkangel Ai

Turn your medical data into AI algorithms without code

About Arkangel Ai

No- code AI as a service platform, that allows healthcare companies to build, deploy, and manage custom AI/ML algorithms at scale and without writing code depending on their needs.

You can see: TEDx talk; Use cases in healthcare, and Democratizing AI for healthcare paper

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Transform data into algorithms to predict, optimize, and give insights in real-time:

- 20x faster algorithm building
- 15x more scalability
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AI Use Cases for Healthcare

- Medication adherence prediction
- Diagnosis diseases prediction
- Treatment access optimization
- Supply chain optimization
- Adverse event prediction
- Clinical deterioration prediction
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Results

350+ hospitals

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35,400+ hours saved

68M+ people covered

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Predict Chronic Kidney Disease

Problem

Chronic Kidney Disease (CKD) is a complex condition in which patients experience excessive cardiovascular and other adverse events and carry a heavy burden of morbidity, mortality, and healthcare costs. An estimated 37 million people—15% of adults—have CKD and another 20–25 million are at risk for developing it (1).

And yet, CKD remains under-recognized by providers and patients, especially in its early stages when patients are largely asymptomatic. Nine in ten adults with CKD are not aware of their condition and one in two people with extremely low kidney function do not know they have CKD (1). Healthcare costs increase dramatically as CKD progresses and in later stages, are five to ten times higher than for someone without CKD (2). These costs are primarily due to hospitalizations resulting from severe complications that often accompany reduced kidney function.

Size of the Problem

- 660,000 people live with kidney failure (3).
- 37 million adults in the U.S. have CKD, a number that has doubled each of the last two decades (1).
- 9 in 10 adults with mild-to-moderate CKD are not aware of their condition and 25% of them (who also have diabetes) will experience rapid progression within two years (1).

Why it matters?

Effective interventions can improve outcomes and reduce healthcare costs. For example, an intervention among beneficiaries of a Maryland health plan reduced hospital admissions by 30 to 45% (depending on CKD stage), readmissions by more than 70%, and costs by 20% (4).To expand the use of value-based programs for CKD, CMS recently announced the Advancing American Kidney Health initiative designed to increase value-based models starting in 2020 (5). AI-based models are ideally suited to help clinicians and care teams in value-based programs by identifying patients to help promote early diagnosis, slow CKD progression, and anticipate and avoid complications and adverse events.

Solution

AI can help you promote early diagnosis, slow the progression of CKD, and anticipate and avoid complications and adverse events. AI helps to identify people with undiagnosed CKD or at risk of rapid progression, predict adverse events due to poor medication adherence, predict CKD-related complications (eg, hyperkalemia), or identify patients who are likely to will start dialysis in the next year.

Data Sources

- Electronic Health Records: EHR data with comprehensive patient histories of vital signs and symptoms, problem lists and chief complaints, tests results, diagnoses and procedures, and prescriptions.
- Remote Monitoring Data: Remote monitoring data capture key vital signs and health behaviors (e.g. blood pressure, heart rate, blood glucose, activity levels, etc.).
- Social Determinants of Health (SDoH): Geo-centric data with details about the social and environmental influences on people's health and outcomes.

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Predict Heart Failure

Problem

Heart failure — sometimes known as congestive heart failure — occurs when the heart muscle doesn't pump blood as well as it should. When this happens, blood often backs up and fluid can build up in the lungs, causing shortness of breath. Certain heart conditions, such as narrowed arteries in the heart (coronary artery disease) or high blood pressure, gradually leave the heart too weak or stiff to fill and pump blood properly.

Proper treatment can improve the signs and symptoms of heart failure and may help some people live longer. Lifestyle changes — such as losing weight, exercising, reducing salt (sodium) in your diet and managing stress — can improve your quality of life. However, heart failure can be life-threatening. People with heart failure may have severe symptoms, and some may need a heart transplant or a ventricular assist device (VAD).

Size of the Problem

- $70 billion is the projected economic cost in 2030 for patients with HF (1).
- 6.5 million adult Americans are living with heart failure (2).
- 10% of HF patients survive 10 years after being diagnosed with HF (3).
- 33% of all Medicare costs are for patients with heart failure (4).

Why it matters?

Today, approximately 6.5 million adult Americans are living with heart failure (HF) (1). By 2030, this is estimated to rise to 8 million people with total economic costs reaching $70 billion at which point 2.97% of U.S. adults will have HF and 71% of them will be age 65 or older (2). With more than one million hospitalizations each year, HF is one of the most common causes of admissions and readmissions and a leading cause of mortality; after a diagnosis of HF, survival estimates are 50% and 10% at five and ten years, respectively (3).

Beneficiaries with HF constitute 10.5% of all FFS Medicare beneficiaries and their costs (excluding medications) make up 33.2% of all Medicare costs (4). HF is a chronic disease characterized by acute exacerbation, and a major cost driver is treatment for worsening HF and fluid overload, 80% of which occurs in inpatient settings (2,3). Many instances of hospitalization for HF patients are considered preventable, yet HF remains the leading cause of hospitalization for patients over age 65 (2,5). HF admissions also generate the highest number and highest rate of 30-day readmissions among Medicare beneficiaries (6,7).

Solution

Organizations can employ predictive analytics to identify high risk HF patients and use insights from AI to enroll patients in care management programs. Proactively identifying high-risk HF patients and intervening to prevent significant exacerbations that cause hospitalization is essential to improving quality of life and reducing avoidable costs. For example, interventions centered on patient self-management have been shown to reduce the odds of readmission after one year by 40% (8). Such programs prevent hospitalizations by strengthening care continuity, improving adherence to complex medication regimens, and ultimately identifying early warning signs more readily.

Data Sources

- Medical Claims: Data extracted from health insurance medical claims with details about dates and place of service, diagnosis codes, key procedures, use of medical equipment, and provider specialties.
- Rx Claims: Data extracted from health insurance pharmacy claims with details about each medication and its type, fill dates, days supply, pharmacy location, and prescribing clinician.
- Electronic Health Records: EHR data with comprehensive patient histories of vital signs and symptoms, problem lists and chief complaints, tests results, diagnoses and procedures, and prescriptions.

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Predict Diabetes

Problem

Diabetes is a chronic disease that occurs either when the pancreas does not produce enough insulin or when the body cannot effectively use the insulin it produces. Insulin is a hormone that regulates blood glucose. Hyperglycaemia, also called raised blood glucose or raised blood sugar, is a common effect of uncontrolled diabetes and over time leads to serious damage to many of the body's systems, especially the nerves and blood vessels.

Size of the Problem

- More than 4000 Americans are diagnosed with diabetes every day (1).
- 88 million Americans have prediabetes (1).
- 2.3x higher average medical expenditures for people with diabetes (3).

Why it matters?

Diabetes affects approximately 34 million adults—more than 10% of Americans—and is the seventh leading cause of death in the United States (1). Uncontrolled diabetes can lead to biochemical imbalances that cause acute life-threatening events and hospitalization (2). Potential complications include significantly increased risk of heart attacks, strokes, kidney failure, lower-limb amputations, and adult blindness. Diabetes is also steadily becoming more common; in the last 20 years, the number of adults diagnosed with diabetes has more than doubled (1). But despite its increasing prevalence, more than one in five people with diabetes are estimated to be undiagnosed and unaware of their condition (1).

Solution

To improve health outcomes and combat costs, providers can leverage predictive analytics to proactively identify patients at high risk for diabetes and patients likely to experience severe complications. This insight can enable cost-effective, proven interventions. Enrollment in comprehensive prevention programs can reduce risk of type 2 diabetes by more than 50%, and interventions based on diabetes self-management education are extremely cost-effective ($5,047/QALY)* compared to routine care (4,5).

Diabetes interventions based on self-management can empower people to dramatically impact their own health (6). Self-monitoring of blood sugar to achieve glycemic control can reduce the risk of eye disease, kidney disease, and nerve disease by 40% (4). Other self-management interventions include adherence to healthy dietary practices and engaging in regular exercise. Additionally, strengthening primary care continuity is critical. Health care services that include regular foot exams can prevent up to 85% of diabetes-related amputations, and regular eye exams can prevent up to 90% of diabetes-related blindness (7,8).

Data Sources

- Electronic Health Records: EHR data with comprehensive patient histories of vital signs and symptoms, problem lists and chief complaints, tests results, diagnoses and procedures, and prescriptions.
- Medical Claims: Data extracted from health insurance medical claims with details about dates and place of service, diagnosis codes, key procedures, use of medical equipment, and provider specialties.

- Social Determinants of Health (SDoH): Geo-centric data with details about the social and environmental influences on people's health and outcomes.

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Predict
COPD

Problem

Chronic obstructive pulmonary disease (COPD) is a chronic inflammatory lung disease that causes obstruction of airflow from the lungs. Symptoms include shortness of breath, coughing, production of mucus (sputum), and wheezing. It is typically caused by long-term exposure to irritating gases or particulate matter, most often cigarette smoke. People with chronic obstructive pulmonary disease are at increased risk of developing heart disease, lung cancer, and several other conditions (1).

Size of the Problem

- Approximately 10% of Canadians aged 35 and over are living with COPD (2).
- Chronic obstructive pulmonary disease (COPD) is the third leading cause of death in the world. In 2019 it caused 3.23 million deaths (3).
- Nearly 90% of COPD deaths in children under 70 years of age occur in low- and middle-income countries (3).

Why it matters?

Air travels down the trachea and reaches the lungs through two large tubes (bronchi). Inside the lungs, these tubes divide many times, like the branches of a tree, into smaller tubes (bronchioles) that terminate in clusters of small air sacs (alveoli) (1). Your lungs rely on the natural elasticity of the bronchi and air sacs to force air out of your body. COPD causes them to lose their elasticity and over-expand, leaving some air trapped in the lungs when exhaling.

As the disease worsens, it is more difficult to carry out normal daily activities, often due to shortness of breath. The disease can have considerable financial consequences due to limited productivity at work and at home and the cost of medical treatment. COPD patients often have other conditions, such as heart disease, osteoporosis, musculoskeletal disorders, lung cancer, depression, or anxiety (3).

Solution

When based on adequate data, database studies can provide useful information on the burden of disease, as well as on the efficacy and safety of treatment in real life, helping to guide decision makers. of decisions. For example, in seven Canadian provinces, electronic medical record (EMR) data from primary care clinics was used to develop predictive models to identify COPD in the Canadian population. The comprehensive nature of this primary care EMR data containing structured numeric, categorical, hybrid, and unstructured text data enables predictive models to capture COPD symptoms and discriminate against diseases with similar symptoms (2).

There, two supervised machine learning models, a multilayer neural network (MLNN) model and extreme gradient boosting (XGB) are applied to identify patients with COPD. The XGB model achieved 86% accuracy on the test data set compared to 83% achieved by the MLNN. Using feature importance, a set of key EMR symptoms to discover COPD was identified, which found medications, health conditions, risk factors, and patient age (2).

Data Sources

- Diagnostic Imaging: Contains information about diagnostic images (for example, CT and MRI).
- Health Services Laboratories: Captures data on hospital, community, and emergency medical services.
- Social Determinants of Health (SDoH): Geo-centric data with details about the social and environmental influences on people's health and outcomes.

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Predict Chronic Diseases

Problem

The United States spends $3.8 trillion annually on healthcare expenditures, 90% of which is spent for people with chronic and mental health conditions (1). Chronic diseases, such as heart disease, cancer, and diabetes, are conditions that last one year or longer and require ongoing medical care, limit a person's activities of daily living, or both.

Size of the Problem

- $3.4 trillion is the total U.S. spending on chronic disease treatment annually (1).
- 10x higher total healthcare costs are incurred by adults with three or more conditions compared to patients with no chronic conditions (2).
- 30% of all adults in the U.S. have three or more chronic diseases (2).

Why it matters?

A staggering 60% of adults have at least one chronic disease and nearly 30% have three or more (1). Managing chronic conditions can be challenging. These conditions do not exist in isolation and frequently occur with other comorbidities. This is especially true for older adults—81% of older adults have at least two chronic conditions and 25% have five or more (2).

The presence of multiple conditions magnifies utilization, costs, and the vulnerability to complications. Adults with three or more conditions are 3.6 times more likely to have an ED visit, 5.3 times more likely to be admitted, have 10 times higher healthcare costs, and fill 36 times more prescriptions than an adult without any conditions (2). They are also 15–18 times more likely to experience physical and social limitations which can lead to functional decline, particularly for older adults, and significantly decrease their quality of life (3). As the population continues to age, the prevalence and impact of chronic diseases is expected to continue to grow.

Solution

Care management programs can mitigate the effects of chronic diseases, prevent adverse events, improve health outcomes, and reduce healthcare costs. Healthcare organizations (HCOs) can use AI to amplify the success of their programs. Predictive analytics enable HCOs to identify high-risk individuals and predict adverse events and potential complications. AI-driven insights also surface specific modifiable risk factors that may have otherwise gone undetected. With these insights, care teams can personalize care plans and improve patient outcomes and quality of life.

Data Sources

- Vital Signs: Data indicating the status of the body’s vital and life-sustaining functions, with core vital signs including blood pressure, pulse, respiration rate, and body temperature.

- EHR Problem Lists: Data capturing the most important problems facing a patient, when it occurred and when it was resolved, and lists other illnesses, injuries and factors that affect their health.

- Remote Monitoring Data: Remote monitoring data capture key vital signs and health behaviors (e.g. blood pressure, heart rate, blood glucose, activity levels, etc.).

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Predict Drug Safety

Problem

Every year, Adverse drug reactions (ADRs) – unintended, harmful events attributed to intended medicine use – result in more than 750,000 inpatient injuries or deaths, affect nearly two million hospital stays, and directly result in over one million ED visits and 125,000 hospitalizations. ADRs are estimated to cause at least 10% of all admissions in older adults.

Size of the Problem

- 750,000 inpatient injuries or deaths are attributed to ADRs annually (1).
- 2x increased incidence of ADRs in older adults (3).
- 3x older adults are three times as likely to die of ADRs (3).
- 20-60% is the prevalence of PIM usage among older adults (7).

Why it matters?

Every year, adverse drug reactions (ADRs) – unintended, harmful events attributed to intended medicine use – result in more than 750,000 inpatient injuries or deaths, affect nearly two million hospital stays, and directly result in over one million ED visits and 125,000 hospitalizations (1,2). Older adults are more vulnerable to ADRs due to aging-related kidney and liver changes that create increased sensitivity and exposure to pharmaceuticals. They experience ADRs twice as frequently as their younger counterparts, and are four times as likely to be hospitalized (3). ADRs are estimated to cause at least 10% of all admissions in older adults, and between 10–39% of hospitalized older adults will experience an ADR (4,5).

They are also more likely to die from ADRs; a recent study found that fatal outcomes were reported approximately three times more often for older adults (6).

One reason for increased risk of ADRs is the use of Potentially Inappropriate Medications (PIMs), particularly for older adults who may be taking multiple medications. Polypharmacy, commonly defined as regular use of five or more medications, and the prevalence of PIMs are strongly associated with increased risk of ADRs in older adults. Alarmingly, the prevalence of PIMs ranges from 20–60% of all older adults depending on healthcare setting and criteria used to define inappropriate prescribing (7). PIM use is associated with a 10–30% increased risk of hospitalization, and older adults with polypharmacy are roughly 80% more likely to be hospitalized within a year relative to equivalent patients without polypharmacy (7,8).

PIMs and polypharmacy can result in considerable cognitive impairment consistent with dementia and may lead to misdiagnosis and further prescriptions, potentially adding to an already-elevated ADR risk. Despite this, opportunities for medication reconciliation and deprescribing are frequently missed. A recent study found that 66% of hospitalized older patients had at least one PIM prescribed at discharge, 49% continued a previously prescribed PIM, 31% were prescribed a new PIM during hospitalization, and ultimately 36% visited the ED, were rehospitalized, or died within 30 days of discharge (9).

Solution

Up to two-thirds of ADRs in hospitalized and multi-morbid older adults are considered preventable, and AI-based models are ideal to help Healthcare organizations (HCOs) identify, anticipate, and avoid these adverse outcomes (7).

Predictive analytics enable HCOs to integrate patient-specific data (e.g., conditions, comorbidities, physiologic vulnerabilities, and medications) with drug burden indices, support continuous monitoring of health and behaviors, and predict individuals at the greatest risk of ADRs. This insight provides care teams with the ability to proactively initiate tailored interventions. For example, interventions designed around deprescribing and reconciling medication use have been shown to reduce ADR risk (7,10)

Data Sources

- Rx Claims: Data extracted from health insurance pharmacy claims with details about each medication and its type, fill dates, days supply, pharmacy location, and prescribing clinician.
- Medical Claims: Data extracted from health insurance medical claims with details about dates and place of service, diagnosis codes, key procedures, use of medical equipment, and provider specialties.
- Health Risk Assessments: Self-reported data from health questionnaires that assess a person's individual medical history, health risks, lifestyle, health behaviors, and quality of life.

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Predict Acute Ischemic Stroke

Problem

Cerebrovascular disease is the fourth leading cause of death among women, the fifth leading cause of death among men, and is a leading cause of serious long-term disability (1). There are nearly 800,000 strokes in the United States each year, and more than 50% of stroke patients are readmitted or die within one year of discharge (2,3). The incidence of stroke increases with age. Approximately 50% occur in people older than 75, and stroke is the second leading cause of hospital admission among the elderly (1,4). Notably, mortality from cerebrovascular disease is increasing significantly among younger adults and has risen by 36% in recent years (1).

Size of the Problem

- More than 50% of stroke patients are readmitted or die within one year of discharge (1).
- Good blood pressure control can prevent up to 40% of strokes (6).
- 90% of stroke survivors are left with residual functional deficits (2).

Why it matters?

The total cost of stroke is immense, averaging approximately $50 billion annually (5). Despite recent improvements in acute stroke treatment, more than one-third of patients are functionally dependent or have died within three months of a stroke.

Moreover, up to 90% of stroke survivors are left with residual functional deficits that significantly impact the quality of life and may increase the risk of further adverse outcomes (2). For example, immobility limits cardiovascular exercise and increases the risk for recurrent stroke and cardiovascular illness. Nearly one in four strokes occur in people who have previously had a stroke (5).

Solution

Preventive interventions that account for modifiable risk factors can potentially reduce the incidence of stroke in high-risk patients. To this end, predictive analytics are critical for proactively and accurately identifying such patients and helping to facilitate proven interventions individually. Interventions that address hypertension—a risk factor for 90% of all strokes—have proven to be effective, and it is estimated that up to 40% of all strokes can be prevented with good blood pressure control (6). Similarly, self-management interventions can significantly reduce risk. Smoking is associated with up to four times increased risk of stroke, and frequent exercise can reduce risk by up to half (6). For patients who have had a stroke, multidisciplinary rehabilitation programs remain the mainstay of treatment to improve outcomes and prevent secondary strokes (2).

Data Sources

- Electronic Health Records: EHR data with comprehensive patient histories of vital signs and symptoms, problem lists and chief complaints, test results, diagnoses and procedures, and prescriptions.

- EHR Problem Lists: Data capturing the most important problems facing a patient, when they occurred and when they were resolved, and lists other illnesses, injuries, and factors that affect their health.
- Medical Claims: Data extracted from health insurance medical claims with details about dates and place of service, diagnosis codes, key procedures, use of medical equipment, and provider specialties.

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Predict Maternal Mortality and Obstetric Outcomes

Problem

The 2020 U.S. maternal mortality rate ranked last among all industrialized countries, and more than 60,000 women suffer from severe maternal morbidity annually. Maternal health data also evinces immense racial and ethnic disparities. Black women are three to four times more likely to die a pregnancy-related death compared to White women. Reducing these disparities is key to improving obstetric outcomes.

Size of the Problem

- 46% of maternal deaths for Black women are considered potentially preventable (1).
- 3-4x higher likelihood of maternal mortality for Black women compared to White women (1).
- More than 60,000 women suffer from maternal morbidity annually in the U.S.(1).
- Roughly 50% of births in 2019 were paid for by Medicaid (2).

Why it matters?

The 2020 U.S. maternal mortality rate ranked last among all industrialized countries, with 17.4 deaths per 100,000 pregnancies (2). For every maternal death measured, 100 women also experience severe obstetric morbidity (1). This is a potentially life-threatening outcome of labor and delivery, often resulting in significant health consequences. More than 60,000 women suffer from severe maternal morbidity annually, and the rate of maternal morbidity increased by 36% from 2008 to 2018 (1,3).

Adverse obstetric outcomes also present a substantial financial burden. Severe maternal morbidity has been associated with an increase in maternity-related costs of 111% in commercially-insured populations and 175% in populations covered by Medicaid (4). Such increases are impactful; there were 3.75 million births in 2019 and Medicaid paid for approximately 50% of them (5,6).

Maternal health data evinces immense racial and ethnic disparities. On average, Black women are three to four times more likely to die a pregnancy-related death compared to White women, and they are up to 12 times more likely in some cities (1). In addition to a dramatically increased mortality rate, Non-Hispanic Black women have the highest rates for the majority of CDC severe morbidity indicators. Black women also have elevated rates of pregnancy-induced and chronic hypertension, asthma, placental disorders, preexisting diabetes, and blood disorders. Minority women are also less likely to have chronic conditions adequately managed prior to pregnancy, and they are more likely to experience complications due to these conditions (1).

Reducing potentially preventable maternal morbidity and mortality hinges on reducing the racial and ethnic disparities. In a study of maternal deaths 46% of black deaths were considered potentially preventable compared to 33% of white deaths (1). In addition to minorities having higher likelihood of chronic conditions during pregnancy, health outcome disparities are correlated with a plethora of socioeconomic-related factors, such as hospital quality. 75% of Black deliveries occur in a quarter of U.S. hospitals, but just 18% of White deliveries occur in the same hospitals (1). On average, these hospitals have higher risk-adjusted maternal morbidity rates.

Similarly, a national survey of women's childbearing experiences found that roughly 25% of respondents experienced discrimination during hospitalization, and Black and Hispanic women were nearly three times as likely to indicate concerns with their treatment due to race, ethnicity, and cultural background (7).

Data Sources

- Medical Claims: Data extracted from health insurance medical claims with details about dates and place of service, diagnosis codes, key procedures, use of medical equipment, and provider specialties.
- Electronic Health Records: EHR data with comprehensive patient histories of vital signs and symptoms, problem lists and chief complaints, tests results, diagnoses and procedures, and prescriptions.
- Social Needs Assessments: Self-reported data that identify an individual's specific needs and the acute social and economic challenges they are experiencing.

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Predict Malaria
In Blood

Problem

Malaria is an acute disease caused by parasites of the genus Plasmodium. Commonly, these parasites are transmitted to people through the bite of infected females. Among the first and most common symptoms are fever, headache, and chills. They are generally difficult to recognize because they can be mild, appearing 10 to 15 days after the bite of the infecting mosquito. However, when the symptoms are not treated, they lead to a serious clinical picture that can lead to death in 24 hours (1).

Size of the Problem

- In 2020, there were 241 million malaria cases, while in 2019, 227 million cases, according to the World Malaria Report (1).
- About ⅔ of this increase is related to service interruptions caused by the COVID-19 pandemic. The other third relates to a change WHO recently introduced in calculating mortality from malaria (1).
- In the African Region, there is a disproportionately high fraction of the global disease burden. In 2020, 95% of malaria cases and 96% of deaths from this disease were concentrated there. Of all these deaths, 80% correspond to children under five years of age (1).

Why it matters?

One of the first tools implemented by WHO over the last two decades is the extension of access to malaria prevention strategies. Particularly effective vector control procedures and the use of preventive antimalarial drugs. This strategy has hardly helped to reduce the global burden of disease. Another basic malaria elimination strategy is vector control.

This is very effective in preventing infection and reducing disease transmission. In this case, the main explosions are the use of insecticide-treated nets and indoor spraying with residual-action insecticides.

Chemoprophylactic treatments are those that use drugs in order to prevent malaria disease and, of course, its consequences. These include intermittent preventive treatment of lactating children and pregnant women, seasonal antimalarial chemoprophylaxis, and mass drug administration. This also includes the rapid diagnosis strategy in case of suspected infection and the treatment of confirmed cases. Finally, we found that since October 2021, the vaccine has been administered to children living in areas with moderate to intense transmission. The vaccine has been proven to significantly reduce the incidence of disease and mortality (1).

Solution

AI is changing the way healthcare services are delivered in various settings. Their processes have been facilitated by the increasing availability of large data sets and novel analytical methods based on them. Despite the multiple attempts to create prevention, diagnosis, and timely treatment strategies by the different health entities, there are problems, such as the appearance of resistance to antimalarial drugs or the early detection of parasites, that reduce the effectiveness of these strategies. This first creates the need for new alternative drugs, for which traditional drug identification approaches are time-consuming and resource-intensive (2).

Second, a light microscopic examination of blood smears is the gold standard for diagnosing malaria. However, this method requires a lot of time and highly qualified personnel to perform the microbiological diagnosis (3). In recent studies, AI has shown accurate performance using structure-based approaches in chemical property prediction. Since some data already exists, AI would be suitable for identifying new drugs. These models can learn patterns within the data and help identify successful and effective compounds. There are also new techniques based on the analysis of digital images using deep learning and artificial intelligence methods, defined as novel alternative tools for the challenging diagnosis of this infectious disease (3).

Data Sources

- National Library of Medicine, National Institutes of Health, Bethesda USA, has blood smears from 150 P.falciparum-derived patients at Chittagong Medical College Hospital (4).
- MP-IDB: The Malaria Parasite Image Database for Image Processing and Analysis has 229 images (5).
- Applying Faster R-CNN for object detection in malaria images, 1364 images with bounding boxes around the parasites (6).

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Prediction of
Antibiotic Resistance

Problem

Antibiotic-resistant bacteria are one of the world's greatest health threats, causing severe problems in preventing and treating persistent disease (1)(2). Despite the various actions taken over the past decades to address this issue, trends in global antibiotic resistance show no signs of slowing (2). The effectiveness of antibiotics is endangered due to inadequate medical prescriptions, excessive use and misuse of these drugs, extensive agricultural use, the availability of few new antibiotics, and regulatory barriers to the development of new medicines by the pharmaceutical industry. As a result, the rapid emergence of resistant bacteria is increasing dangerously high worldwide, leading to the antibiotic resistance crisis (3).

Size of the Problem

- 30-50% of treatment indications, agent choice, or duration of antibiotic therapy are incorrect (3).
- 30-60% of antibiotics prescribed in UCIs are unnecessary, inappropriate, or suboptimal (3).
- 80% of antibiotics sold in the U.S. are used in animals to promote growth and prevent infections (3).
- 27% of all drugs sold without prescription in urban areas, while this dropped to 8% in rural areas (4).
- 51.7% of pharmacies dispense antibiotics freely without a prescription (4).

Why it matters?

Antibiotic resistance increases morbidity and mortality associated with infections and contributes significantly to rising healthcare costs due to longer hospital stays, increased hospital admissions, and the need for more costly second-line medications (1)(5). Indeed, resistance results from the interaction of microorganisms, patients, the hospital environment, and antibiotics and infection control practices (5). Antibiotic resistance is seen as a major threat as it compromises the ability of the human immune system to deal with infectious diseases and contributes to a variety of complications in vulnerable patients and patients suffering from chronic conditions (2).

Antibiotics are the second most self-medicated drugs after painkillers (3). Antibiotic self-medication predisposes patients to pharmacological interactions; the symptoms of an underlying disease can be ignored, resulting in a high probability of developing microbial resistance (6). Unbridled irrational use of antibiotics without prescription or medical guidance may increase the likelihood of inappropriate, incorrect, or inappropriate therapy, misdiagnosis, delays in proper treatment, pathogen resistance, and increased morbidity (7).

Solution

Predictive analytics and AI may assist clinicians in monitoring trends in antimicrobial resistance to promote sensible applications of antibiotics (8). AI-based models could recognize and predict the severity of infection, provide for appropriate antibiotic prescription including appropriate therapy selection, dose, and correct route of administration, and classify and predict bacterial resistance to antibiotics by genomes (9).

In addition, ML techniques can predict early antibiotic resistance or the probability of a microbial agent becoming resistant. Another application of AI to antibiotic resistance in the healthcare industry could be the discovery of new antibiotics structurally different from those already known (8).

Data Sources

- Genomic data resource: Data extracted from the accumulation of genomes in clinical laboratories that can be used to survey the evolution of pathogens.
- Unstructured Clinical Registries: Data extracted from integrated patient EHR registries contain different patient-level variables such as demographics, diagnoses, problem lists, medications, vital signs, and laboratory data.

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Operational

Section

Improve Supply Chain Management

Problem

The crucial aim of Supply Chain Management (SCM) within the pharma industry is to make the right product, for the right customer, in the right amount, at the right time (1). And that process carries out many challenges in the operational part regarding real-time data collection and developing sustainable methodologies to optimize the use of resources and avoid waste of materials and products.

Size of the Problem

- According to the IQVIA Institute for Human Data Science, the biopharma industry loses $35 billion USD annually due to temperature-control failures across supply chains (2).
- 90% pharma manufacturers reported that they didn't have full visibility into their supply chains and didn't trust the in-transit data they were receiving (3).
- The pharmaceutical industry spends about $1 billion per year on energy expenses and produces 55% more emissions than the automotive industry (4).

Why it matters?

The SCM has a lot of data-heavy and monotonous work that implies money and time for the pharmaceutical and medical device industry. As an example, filing paperwork manually can cost businesses 6,500 hours a year, a substantial time loss that affects productivity. AI can take care of these administrative jobs, freeing human employees to work on other projects at the same time (5).

Not only that, that inefficiency provokes the waste of resources and materials, where only in Latam there is a loss of 700 Million USD in drugs that expired out of the overstock in the warehouses (6).

Solution

AI systems can use past trends and market signals to forecast demand. Warehouse managers can use them to see what they need to store more or less of. They could then avoid surplus and deficit, maintaining a consistently prepared operation. Thus, pharma manufacturers will have a full report of the dynamics of demand, storage and production of their products that will allow a better operation and decision-making process. Moreover, AI predictions about customer demands will help to fill orders faster, prioritize shipments, optimize route planning and inventory management (5,7).

It has been demonstrated that early adopters of AI in supply chain management saw a decrease in logistics costs of 15%, an increase in inventory levels of 35%, and a boost in service levels of 65% (7).

Data Sources

- Inventory Records: information about the products that come into the warehouse, leave the warehouse and remain within the warehouse.
- Demand records: historical data of the regional sales where the warehouse is located.
- Production data: self-reported data of the amount of product that comes from fabric.

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Arkangel Ai

Predict Length of Stay

Problem

Every year, over 35.7 million hospital stays in the U.S. total over $415 billion in annual healthcare spending. The average length of stay (LOS) is 4.6 days. If it can be safely reduced, in addition to curbing excess spending, eliminating unnecessary hospital days can significantly improve patient health outcomes.

Size of the Problem

- Over $415 billion is attributed to hospital stays annually (1).
- 7x increased cost is attributed to prolonged LOS for elderly ICU patients compared to those without extended LOS (3).
- $11,700 is the average cost of an inpatient stay in the U.S. (1).
- More than half a day is the additional LOS Medicare patients experience on average relative to the general population (1).

Why it matters?

Every year, more than 35.7 million hospital stays in the U.S. total over $415 billion in annual healthcare spending (1). The average length of stay (LOS) is 4.6 days. If it can be safely reduced, in addition to curbing excess spending, eliminating unnecessary hospital days can significantly improve patient health outcomes. Excessively long stays may lead to unforeseen complications that impact care, including increased risk for hospital-acquired conditions (HACs) and infections, reduced ability to provide immediate care to other patients due to reduced capacity, and an inability to allocate healthcare resources efficiently.

Delays in discharge often lead to prolonged LOS and create clinical and operational burdens on providers. As long as patients continue to occupy beds while awaiting discharge, clinical personnel must attend to them, reducing the amount of time they can spend with other patients that may require more intensive care. This leads to greater scarcity of beds and delays operational processes, such as sanitizing rooms and medical equipment before subsequent use. Further, extended LOS can increase risk for HACs in more vulnerable patients, and may also result in “access block”—a situation in which patients requiring admission are forced to wait for more than eight hours in the emergency department due to lack of available inpatient beds (2). Access block occurs for approximately 8% of patients and perpetuates extended LOS; it is associated with nearly a day of increased LOS on average.

The impact of prolonged LOS on health outcomes is especially pronounced in the ICU setting and is associated with greater incidence of adverse events for vulnerable patients, such as older adults. Elderly ICU patients generally require more resource-intensive treatment, and roughly 55% that experience a prolonged LOS die within six months of discharge (3). These patients also incur approximately seven times the cost of patients that do not experience a prolonged LOS.

Solution

AI-based models are ideally suited to help healthcare organizations (HCOs) reduce LOS and improve health and financial outcomes. Leveraging AI, HCOs can accurately predict patient LOS, surface individual patients that are appropriate for discharge, and assess patient-specific risk factors to help triage and streamline care. Teams across the organization can use AI-driven insights to improve resource management planning, reduce patient vulnerability, optimize hand-off procedures and communication, and accelerate the discharge process.

Data Sources

- Medical Claims: Data extracted from health insurance medical claims with details about dates and place of service, diagnosis codes, key procedures, use of medical equipment, and provider specialties.
- ADT Records: Data from Admit, Discharge, and Transfer feeds and patient data notification services that synchronize patient demographic, diagnostic, and visit information across healthcare systems.
- Care Quality: Data with details from CMS Hospital Compare and other quality measures related to timely and effective care, complications, and readmissions and deaths.

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Generative Artificial

Intelligence

Medical Research Copilot

Problem

Staying updated with the latest research and advancements in the medical literature is vital for healthcare professionals to deliver high-quality care. However, the ever-expanding body of medical knowledge poses significant challenges, particularly regarding the time required to review and assimilate this information. Doctors face substantial time constraints due to their demanding work schedules, patient care responsibilities, and administrative tasks, which can impede their ability to dedicate sufficient time to stay up-to-date with the latest research findings. This limitation hampers their ability to provide the most current and evidence-based care, potentially impacting patient outcomes and the overall quality of healthcare delivery.

Why it matters?

- Time Constraints: Doctors are confronted with heavy workloads, including patient consultations, diagnostic assessments, treatment planning, and documentation tasks. As a result, they have limited time to keep up with the vast and ever-growing body of medical literature. Reviewing research articles, attending conferences, and staying abreast of emerging discoveries requires significant time and effort. With the demands of clinical practice, doctors often find it challenging to allocate sufficient time for comprehensive literature reviews, resulting in potential gaps in their knowledge and an inability to incorporate the latest evidence into their practice.

• Information Overload: The volume of medical literature published is increasing at an unprecedented rate, with new studies, clinical trials, and research findings emerging constantly. This wealth of information can be overwhelming for doctors to navigate and process effectively. The sheer volume and diversity of sources make it difficult to identify relevant and trustworthy research articles, leading to the risk of missing critical updates or relying on outdated information. Doctors face the challenge of distinguishing between high-quality studies and potentially biased or flawed research, further complicating their efforts to stay updated with the latest evidence.

• Translation and Application: Even when doctors have access to the latest research, another challenge lies in effectively translating and applying this knowledge to their clinical practice. Research findings often need to be contextualized, considering patient-specific factors, clinical guidelines, and individual treatment goals. Doctors must integrate the evidence into their decision-making process, aligning it with their clinical experience and patient preferences. This process requires time, critical thinking, and a deep understanding of both the research and its application in real-world healthcare scenarios.

Solution

To address the challenge of staying updated with the latest research in medical literature, a custom-made AI copilot can be developed, leveraging the capabilities of a Language Model (LLM) trained on medical literature. This AI copilot would serve as a reliable and efficient resource for doctors to obtain factual and evidence-based insights from medical literature. By utilizing its extensive knowledge base, the AI copilot can swiftly process and extract relevant information, providing doctors with concise and accurate answers to their questions.

It can assist in retrieving up-to-date research findings, summarizing key points, and offering insights into the application of evidence-based practices. By empowering doctors with instant access to the latest medical literature, the AI copilot can save time, enhance knowledge acquisition, and enable informed clinical decision-making, ultimately improving patient care and outcomes.

Data Sources

- Medical Literature
- Peer review journals

Citations

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Discharge Note
Copilot

Problem

The process of writing discharge notes by doctors in hospitals is currently plagued by two major issues: excessive time consumption and increased risk of patient infection. These problems arise due to the additional time required for hospitalization and the potential transmission of infections. Addressing these concerns is essential to streamline the discharge process, optimize healthcare provider productivity, and prioritize patient safety.

Why it matters?

- Excessive Time Consumption: Doctors face significant challenges when writing discharge notes, primarily due to the increased complexity and length of documentation required for hospitalized patients. The prolonged hospital stay necessitates more comprehensive and detailed notes encompassing medical history, treatment plans, medication instructions, and follow-up recommendations. As a result, doctors spend an inordinate amount of time meticulously crafting these notes, detracting from their availability for other patient care activities. This leads to inefficiencies, delays in patient discharge, and potential hospital backlogs.

- Increased Risk of Patient Infection: Extended hospitalization exposes patients to a heightened risk of acquiring healthcare-associated infections. The time spent in a hospital setting puts individuals closer to pathogens and increases the likelihood of transmission. As key healthcare providers, doctors spend considerable time in patient rooms, interacting with potentially contagious individuals and touching various surfaces. Consequently, the increased exposure to infectious agents elevates the possibility of doctors inadvertently transmitting infections to subsequent patients when writing discharge notes.

- Both these issues compromise the quality of healthcare delivery and patient outcomes. The protracted discharge note-writing process strains healthcare resources, affecting patients' timely discharge and doctors' ability to attend to other critical duties. Moreover, the augmented risk of patient infection threatens the fundamental principle of healthcare: to 'do no harm.' Thus, it is imperative to devise interventions that address the excessive time spent on discharge note writing while concurrently mitigating the potential transmission of infections to safeguard patient safety and optimize healthcare operations.

Solution

To address the challenges associated with the time-consuming process of writing discharge notes in hospitals and the increased risk of patient infection, an AI-powered Language Model (LM) can assist doctors in drafting comprehensive and accurate discharge notes. Leveraging the capabilities of a Large Language Model (LLM), doctors can provide prompts and receive real-time assistance in generating the necessary documentation.

Data Sources

- Patient information

Citations

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Arkangel Ai

Few Shot Disease Classification Copilot

Problem

Accurate disease classification is essential for effective healthcare management, research, and resource allocation. However, the process becomes increasingly challenging and expensive when data is lacking, particularly for underrepresented diseases and populations. Inadequate data hinders the development of robust classification models, leading to misdiagnoses, delayed treatments, and insufficient understanding of disease patterns and prevalence. This poses significant challenges for healthcare providers, researchers, and policymakers, limiting their ability to address the specific needs of underrepresented diseases and populations.

Why it matters?

- Insufficient Data Availability: Many diseases, particularly rare or underrepresented conditions, lack sufficient data due to their low prevalence or limited research focus. This scarcity of data makes it difficult to establish accurate and comprehensive disease classification systems. Without a substantial dataset, it becomes challenging to identify distinctive patterns, subtypes, or factors that differentiate one disease from another. The lack of data poses a significant hurdle in developing effective classification models, hindering accurate diagnosis and appropriate treatment selection.
- Limited Representation of Underrepresented Diseases and Populations: Certain diseases disproportionately affect specific populations, such as ethnic minorities, marginalized communities, or individuals from low-income regions. However, data collection efforts often overlook these populations, resulting in a lack of representation in disease classification systems.

Limited representation leads to biased and incomplete models that may not accurately reflect these underrepresented groups' disease profiles or outcomes. The lack of diverse data restricts the understanding of disease progression, response to treatment, and the development of tailored interventions for these populations.

- Cost and Resource Intensiveness: Collecting and curating data for disease classification can be resource-intensive and expensive. Gathering data from diverse sources, such as electronic health records, clinical trials, or population surveys, requires significant investment in infrastructure, personnel, and technology. The challenges are amplified for underrepresented diseases and populations due to the scarcity of data sources and the need for targeted data collection efforts. The cost and resource requirements associated with data collection, standardization, and analysis present barriers to developing comprehensive and representative disease classification systems.

Solution

A solution can be developed using LLM (Language Model) and a custom-made AI system to address the challenges of limited data and underrepresentation in disease classification. By leveraging the vast knowledge and language processing capabilities of the LLM, coupled with a tailored AI system, it becomes possible to classify diseases accurately and account for underrepresented diseases and populations. The LLM can be trained on diverse medical literature, clinical guidelines, and patient records to understand various diseases comprehensively. The custom AI system can integrate additional data sources and address specific disease profiles that lack sufficient representation.

By harnessing these technologies, healthcare professionals can benefit from improved disease classification accuracy, identification of subtypes, and tailored treatment recommendations. For example, the solution can accurately classify rare diseases by leveraging the collective knowledge of the LLM and complementing it with specialized data collection efforts. By incorporating underrepresented diseases and populations in the training and validation process, the custom AI system can ensure more equitable representation, improving healthcare outcomes for all individuals, regardless of the rarity or underrepresentation of their condition.

Data Sources

- Historical disease symptoms
- A few patient examples with correct labels

Citations

1. Decherchi S, Pedrini E, Mordenti M, Cavalli A, Sangiorgi L. Opportunities and Challenges for Machine Learning in Rare Diseases. Front Med (Lausanne). 2021 Oct 5;8:747612. doi: 10.3389/fmed.2021.747612. PMID: 34676229; PMCID: PMC8523988.

Paper Summarization Copilot

Problem

Doctors recognize the importance of keeping up with the latest medical literature to stay informed and provide evidence-based care. However, searching, reading, and evaluating research papers is time-consuming and frustrating when doctors discover that the literature they invested time in does not meet the relevant or high-quality criteria. This poses a significant challenge, as doctors must navigate a vast amount of published research to find the most reliable and applicable studies. The limited time available for literature review, coupled with the difficulty in discerning the credibility and relevance of papers, results in wasted efforts, delayed access to valuable information, and potential gaps in knowledge that can affect patient care.

Why it matters?

- Time Constraints: Doctors have demanding work schedules, including patient consultations, procedures, administrative tasks, and teaching responsibilities. As a result, they have limited time for a thorough literature review. Searching for relevant papers, reading them in detail, and critically evaluating their methodology, results, and implications requires significant time investment. Time constraints may force doctors to skim through papers or rely on abstracts and summaries, risking an incomplete or inaccurate understanding of the research.

- Difficulty in Identifying Relevance: The volume of medical literature published is staggering, with new research studies emerging rapidly. Doctors often struggle to identify the most relevant papers that address their specific areas of interest or patient populations.

Searching through databases, sorting through search results, and assessing article titles and abstracts can be time-consuming and may result in doctors selecting papers that are not directly applicable to their practice or research needs. This wastes time and effort reading papers that do not provide the desired information.

- Evaluating Paper Quality: Ensuring the reliability and credibility of research papers is essential for evidence-based practice. However, doctors face challenges in determining the quality of papers without investing significant time in reading them in detail. Assessing factors such as study design, sample size, statistical methods, and potential biases can be complex and time-consuming. Doctors may spend valuable time on poorly designed papers, lack robust methodology, or have limited relevance to their clinical practice.

Solution

AI can be employed to summarize research papers efficiently. The LLM can automatically analyze and extract key information from research papers by leveraging its language processing capabilities and access to extensive medical literature. It can generate concise summaries highlighting the research objective, methodology, findings, and implications. These summaries serve as efficient and time-saving resources for doctors, giving them a quick overview of the paper's content and relevance. By utilizing LLM-powered research paper summarization, doctors can streamline their literature review process, quickly identify the most valuable papers, and allocate more time to critically evaluating and applying the research in their clinical practice.

Data Sources

- Research papers

Citations

1. Alper BS, Hand JA, Elliott SG, Kinkade S, Hauan MJ, Onion DK, Sklar BM. How much effort is needed to keep up with the literature relevant for primary care? J Med Libr Assoc. 2004 Oct;92(4):429-37. PMID: 15494758; PMCID: PMC521514.

Summarize Medical Encounter Copilot

Problem

Doctors face significant challenges writing comprehensive and accurate encounter notes after patient consultations. Documenting detailed information about the patient's condition, medical history, diagnosis, treatment plan, and other relevant factors is time-consuming and can lead to errors. The combination of limited time availability and the complexity of capturing and synthesizing information poses significant challenges, potentially leading to incomplete or inaccurate encounter notes, compromised continuity of care, and increased risk of medical errors.

Why it matters?

- Time Constraints: Doctors have demanding schedules and often face time pressures due to the high volume of patients they need to see. This limited availability leaves them with inadequate time to write thorough and comprehensive encounter notes. Documenting relevant details, including medical history, physical examination findings, and treatment recommendations, requires careful attention and consideration. Time constraints may force doctors to rush through the documentation process, leading to incomplete or hasty encounter notes that may lack critical information.

- Cognitive Burden and Information Overload: Writing encounter notes requires doctors to recall and synthesize vast amounts of information gathered during the patient consultation. The cognitive burden of capturing the complexity of the patient's condition, medical history, and relevant observations can be overwhelming. Doctors must process and organize multiple pieces of information while maintaining accuracy and clarity.

The cognitive load and information overload may increase the likelihood of errors, including omissions, inaccuracies, or inadequate documentation of critical details.

- Standardization and Clarity: Encounter notes must follow certain guidelines and be structured in a standardized format to ensure clarity and effective communication among healthcare providers. However, doctors may encounter challenges adhering to these guidelines, especially when time is limited or specific details require careful articulation. Lack of standardization and clarity in encounter notes can hinder effective collaboration, care handover, and treatment continuity, potentially leading to misunderstandings or errors in subsequent healthcare encounters.

Solution

An LLM (Language Model) can be leveraged to automate the generation of comprehensive and accurate encounter notes to address the challenges of time constraints and potential errors in writing encounter notes. By leveraging its language processing capabilities and understanding of medical terminology, the LLM can analyze patient data, clinical observations, and treatment plans to generate structured and standardized encounter notes. It can extract relevant information from electronic medical records, identify key details, and synthesize them into a cohesive narrative. This AI-powered solution reduces the time burden on doctors, ensures consistency in documentation, and minimizes the risk of errors or omissions. By utilizing LLM-generated encounter notes, doctors can focus more on patient care while providing thorough and accurate documentation for effective communication and continuity of care.

Data Sources

- Encounter transcription data

Citations

1. Zuger A. Physician Time Spent Using the Electronic Health Record During Outpatient Encounters. Ann Intern Med. 2020 Oct 6;173(7):593-594. doi: 10.7326/L20-0276. PMID: 33017555.

Arkangel Ai

Electronic Medical Record Summarization Copilot

Problem

Doctors often face the challenge of reviewing extensive medical records when assessing a patient's health history and treatment needs. However, thoroughly reviewing these lengthy records is time-consuming and can increase the likelihood of errors. The combination of limited time availability and the complexity of medical records poses significant challenges, potentially leading to missed or misunderstood information, compromised patient care, and increased risk of medical errors.

Why it matters?

• Time Constraints: Doctors have busy schedules and a high volume of patients to attend to, leaving them with limited time to review comprehensive medical records. The extensive documentation, including patient histories, diagnostic reports, test results, medication records, and treatment plans, can be overwhelming to analyze thoroughly within the available time frame. Time constraints may force doctors to skim through records or rely on incomplete information, potentially leading to overlooked details or inadequate understanding of the patient's medical history.

• Cognitive Overload and Information Fatigue: Lengthy medical records can present an information overload challenge to doctors, leading to cognitive strain and potential information fatigue. The volume and complexity of the documentation can overwhelm doctors, making it difficult to process and retain all the relevant information accurately. As a result, doctors may struggle to identify critical patterns or correlations within the medical history, increasing the risk of missing important details or making erroneous assumptions.

● Proneness to Errors: The combination of time constraints, cognitive overload, and the intricate nature of medical records contributes to an increased likelihood of errors during the review process. Doctors may unintentionally misinterpret or overlook crucial information due to limited time or cognitive strain. Inaccurate assessments, incorrect diagnoses, or improper treatment decisions can result from these errors, jeopardizing patient safety and well-being.

Solution

By leveraging AI, its language processing capabilities, and its understanding of medical terminology, the LLM can analyze and extract key information from the EMR. It can generate concise summaries that capture the patient's medical history, relevant diagnoses, treatment plans, and significant findings. These summaries serve as valuable resources for doctors, allowing them to quickly grasp the essential details within the EMR and make informed decisions. By utilizing LLM-powered EMR summarization, doctors can optimize their time, reduce cognitive load, and enhance their ability to provide comprehensive and accurate patient care based on a thorough medical history.

Data Sources

- Electronic medical record

Citations

1. Overhage JM, McCallie D Jr. Physician Time Spent Using the Electronic Health Record During Outpatient Encounters: A Descriptive Study. Ann Intern Med. 2020 Feb 4;172(3):169-174. doi: 10.7326/M18-3684. Epub 2020 Jan 14. Erratum in: Ann Intern Med. 2020 Oct 6;173(7):596. PMID: 31931523.

Arkangel Ai

Disease Protocol
Copilot

Problem

Infertility is a complex medical condition that affects millions of couples worldwide, presenting significant challenges in healthcare. However, the management of infertility is hindered by several critical factors, including inadequate healthcare professional training, limited personalization of treatment plans, and a lack of comprehensive knowledge in this specialized field. These challenges contribute to suboptimal outcomes, increased patient distress, and a need for more effective strategies to address infertility and support affected individuals and couples.

Why it matters?

- Lack of Training: Healthcare professionals, including general practitioners and even some specialists, often receive limited training in diagnosing and treating infertility. As a result, they may lack the expertise to accurately assess infertility factors, identify underlying causes, and recommend appropriate treatment options. This knowledge gap can lead to delays in diagnosis, ineffective treatment plans, and increased patient frustration.

- Limited Personalization: Infertility is a highly individualized condition, influenced by various factors such as age, medical history, lifestyle, and specific reproductive challenges. However, the current healthcare system often falls short in providing personalized treatment approaches. Standardized protocols and a lack of tailored interventions can result in a one-size-fits-all approach that may not address the unique needs and circumstances of each patient. This lack of personalization may lead to suboptimal treatment outcomes, unnecessary procedures, and emotional distress for individuals and couples seeking fertility support.

- Knowledge Gap: The field of infertility is continuously evolving, with advancements in reproductive medicine, assisted reproductive technologies, and scientific research. However, healthcare professionals may struggle to keep pace with the latest developments and evidence-based practices due to a lack of comprehensive knowledge in this specialized field. This knowledge gap can hinder the accurate diagnosis of complex infertility cases, limit access to innovative treatment options, and compromise the quality of care provided to patients.

Solution

Using a combination of generative AI and proprietary knowledge you can generate a custom-built AI copilot that can specifically assist medical specialists in reducing errors. This AI copilot would provide healthcare professionals with a reliable and accessible resource to answer specialized questions in a factual and evidence-based manner. By utilizing its extensive knowledge base, the AI copilot can support healthcare professionals in making informed decisions, improving the accuracy of diagnoses, and tailoring treatment plans based on the latest research findings and best practices. With its ability to process and interpret vast amounts of medical literature, the AI copilot can bridge the knowledge gap, ensuring that healthcare professionals have access to up-to-date information and enabling personalized, evidence-based care for individuals and couples experiencing infertility.

Data Sources

- Medical Protocols
- Peer review journals
- Private infertility protocols design for local conditions

Citations

1. Dehghan A, Abumasoudi RS, Ehsanpour S. Identification and assessment of common errors in the admission process of patients in Isfahan Fertility and Infertility Center based on "failure modes and effects analysis". Iran J Nurs Midwifery Res. 2016 Nov-Dec;21(6):646-651. doi: 10.4103/1735-9066.197674. PMID: 28194208; PMCID: PMC5301075.

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